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The Impact of Machine Learning Algorithms on Improving the Predictive Ability of Accounting Information as Business Partners: An Empirical Evidence from Egyptian listed firms

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Abstract:

This study is designed to provide empirical evidence on the impact of machine learning algorithms on the Predictive Ability of Accounting Information, by investigating the predictive ability of machine learning algorithms as opposed to traditional prediction models that rely on accounting information, on the accuracy of stock price predictions. It also aims to investigate whether machine learning algorithms' predictive ability outperforms traditional prediction models' predictive ability in cash-holding prediction models. Additionally, this study seeks to explore the practical potential of integrating machine learning algorithms and accounting information into prediction models to improve the predictive ability of accounting information. To fulfill this study's expected objectives, the researcher used several approaches. Using a **case study approach compared event study approach**, the comparative analysis results revealed that accounting information's predictive ability was more accurate than the machine learning algorithms' predictive ability in stock price predictions. This suggests that using machine learning algorithms does not necessarily result in better prediction performance and that machine learning algorithms are not the replacement for accounting information in financial predictions.

using the empirical approach, 564 firm-year observations from 2019 to 2022 are analyzed to predict cash-holding. The researcher employed several algorithms such as decision trees, support vectors, and K-nearest neighbor, compared to multiple linear regression based on accounting information as prediction models. The empirical results showed that decision trees as complex algorithms were proven to yield higher accuracy. While, other prediction models, MLR, KN, and SV had (RMSE) and low R^2, which indicates the Low accuracy of predictions. **Also, the empirical results reported** that accounting information significantly affects the accuracy of machine learning algorithms regarding cash-holding predictions. Hence, the current study adds empirical evidence to related previous literature review through emphasizing the complementary nature between the roles of machine learning algorithms and accounting information in financial predictions. Machine learning algorithms must be considered a supporting tool to enhance the predictive ability of accounting information, not a replacement for it. At the same time, accounting information improves the accuracy of machine learning algorithms' predictions. Therefore, it has become necessary for accountants to master machine learning skills to maintain their jobs and assume new roles in the era of artificial intelligence.

Keywords:
Machine Learning Algorithms; predictive ability; accounting information; stock price; cash holding prediction

ملخص البحث:

الهدف الرئيسي من هذه الدراسة هو تقديم أدلة تجريبية بشأن تأثير خوارزميات التعلم الآلي على المقدرة التنبؤية للمعلومات المحاسبية، من خلال التحقيق مما اذا كانت المقدرة التنبؤية خوارزميات التعلم الآلي مقارنة بنماذج التنبؤ التقليدية التي تعتمد على المعلومات المحاسبية، أكثر دقة في التنبؤ بأسعار الأسهم. كما تهدف الدراسة أيضاً إلى التحقق مما إذا كانت القدرة التنبؤية لخوارزميات التعلم الآلي تتجاوز نماذج التنبؤ التقليدية في نماذج التنبؤ بشأن التنبؤ بالاحتفاظ بالنقدية. وبالإضافة إلى ذلك، تسعى هذه الدراسة إلى التحقق مما اذا كان دمج خوارزميات التعلم الآلي والمعلومات المحاسبية في نماذج التنبؤ يؤدى الى تحسين القدرة التنبؤية للمعلومات المحاسبية. ولتحقيق الأهداف المتوقعة من هذه الدراسة، استخدم الباحث مداخل متعددة .باستخدام مدخل دراسة الحالة مقارنة بمدخل دراسة الحدث، كشفت نتائج التحليل المقارن أن المقدرة التنبؤية للمعلومات المحاسبية أكثر دقة من المقدرة التنبؤية لخوارزميات التعلم الآلي عند التنبؤ بأسعار الأسهم. ويدل ذلك على أن استخدام خوارزميات التعلم الآلي لا يؤدي بالضرورة إلى تنبؤات مالية أكثر دقة. وأن خوارزميات التعلم الآلي ليست بديلاً عن المعلومات المحاسبية كمدخلات في نماذج التنبؤات المالية .

وباستخدام المدخل التطبيقي، تم تحليل 564 Firm-Year observations خلال الفترة من 2019 إلى 2022 للتنبؤ بالاحتفاظ بالنقدية. واستخدم الباحث عدة خوارزميات مثل أشجار القرار، وناقلات الدعم، و-K Neearest، ومقارنتها مع الانحدار الخطي المتعدد القائم على معلومات المحاسبة كنماذج للتنبؤ. وأظهرت النتائج أن جميع نماذج التنبؤات لها جذور أعلى متوسط الخطأ التربيعي (RMSE) وأدنىR2 ، مما يدل على انخفاض دقة التنبؤات لهذه النماذج. بينما ثبت أن أشجار القرار كخوارزميات معقدة تحقق درجة أعلى من الدقة. ولذلك، فإن استخدام خوارزميات متقدمة من تعلم الألى قد تؤدى إلى تنبؤات أكثر دقة بالاحتفاظ بالنقدية. كما أظهرت النتائج أن المعلومات المحاسبية تؤثر تأثيراً كبيراً على دقة خوارزميات المتعلقة بالاحتفاظ بالنقدية. ومن ثم، تضيف الدراسة الحالية أدلة عملية إلى الأدبيات السابقة ذات الصلة، من خلال ابراز مدى أهمية التكامل بين كل من خوارزميات التعلم الآلي والمعلومات المحاسبية في نماذج التنبؤات المالية. واعتبار خوارزميات التعلم الآلي أداة داعمة تحسن من القدرة التنبؤية للمعلومات

المحاسبية، وليست بديلاً عنها. وفي الوقت نفسه، تحسن المعلومات المحاسبية دقة تنبؤات خوارزميات التعلم الآلي. ولذلك، أصبح من الضروري للمحاسبين أن يتقنوا مهارات التعلم الآلي في مجال المحاسبة للحفاظ على وظائفهم واضطلاعهم بأدوارهم الجديدة في عصر الذكاء الاصطناعي.

الكلمات المفتاحية: خوارزميات التعلم الآلي، المقدرة التنبؤية، المعلومات المحاسبية، أسعار الأسهم، الاحتفاظ بالنقدية

1. Introduction:

It is widely acknowledged that the purpose of accounting systems is to provide current and potential users of financial reports with useful accounting information regarding the influence of economic events on the company's cash flows, profit, and financial position (Handayani & Wiksuana, 2020). This information assists the stakeholders in their economic decision-making such as decisions granting or repaying loans, and other credit decisions, as well as decisions purchasing, or selling stock, and other investment decisions (Ebaid, 2022). To achieve this purpose, financial reports must be prepared per a Conceptual Framework for Financial Reporting to achieve this purpose. According to this Framework, Accounting information must be relevant to be valuable in making decisions. Where, Relevance refers to how useful accounting information is for financial reports' users to make differences in their economic decisions (IASB, 2018).

According to Imhanzenobe (2022), accounting information is relevant if stock prices are influenced by this information. For accounting information to be relevant, it must have a confirmatory value and predictive value. Confirmatory value provides information regarding historical events, meanwhile predictive value provides forecasts regarding future events. Consequently, accounting information is relevant if it can provide information about past events and help predict future events to react proactively to them (IASB, 2018). In this context, IASB (2018) defined Predictive value as is an enhanced qualitative characteristic that enhances the relevance of accounting information, and accounting information has predictive value if it can be used as an input in the financial prediction models to predict future outcomes by users of financial reports.

Relevant accounting information has several advantages for financial reports' users. it is considered a core benchmark for analyzing and evaluating financial performance and solvency to predict future earnings, cash holding, stock prices, as well as managing operations and supporting decision-making (Ali, 2019). It also contributes to setting organizational strategies and targets through planning growth, resource allocations, and management risks to enhance the effectiveness of the operational processes in the business environment (Nissim, 2022). Despite these advantages, Using accounting information in traditional prediction models has only yet to become sufficient for financial predictions, financial analysis, cash management, and risk management in a business environment driven by technological advancement. This is because accounting systems are not able to process big data. Traditional accounting systems are time-consuming and expertly labor-intensive in processing big data, which negatively influences accounting information's relevance. In contrast, Machine learning algorithms can deal with big data immediately and efficiently (Zemankova, 2019; Lee & Tajudeen, 2020; Jin et al., 2023). Summarizing, these algorithms can help accountants analyze big data to determine patterns and generate knowledge related to big data, which, in turn, supports the predictive ability of accounting information in financial predictions, leading to improved accounting information’s relevance (Brennan et al., 2017).

In other means, for accounting information to effectively fulfill its role in such a highly uncertain and competitive environment, accountants must adopt technological advancements tools and accounting software to perform their daily tasks. This implies that the advent of advanced software accounting and automation technologies lead to the role of accountants has evolved beyond traditional number-crunching to encompass strategic financial predictions and analysis (Askary et al., 2018; Breuer & Schutts, 2021). Technological advancements enable prepared real-time financial reporting and analysis effectively by automating repetitive tasks like data entry, bookkeeping, recording, transaction categorization, and reconciliation. As well as exploiting the accountants' time to concentrate on complex accounting tasks that require more professional judgment to prepare the relevant estimates and forecasts. In turn, leads to enhanced efficiency prepared accounting estimates, detecting fraud, auditing, taxation, and financial prediction (Özlem & Tan, 2022). These advantages collectively provide accurate and relevant timely insights about companies' financial performance to stakeholders and allow for seamless access to financial information that comprehensively overviews the financial position and performance of companies. Additionally, disclosures related to nondiscretionary accruals and accounting estimates support financial analytics and prediction facilitating better stakeholder decision-making (Nissim, 2022).

The accounting profession is characterized by continuous development and intense competition among practitioners. In this context, Professional accountants' roles have evolved from traditional bookkeepers to more dynamic ones to accommodate the fast changes in the dynamic environment, such as digital economics, e-commerce, online business transactions, and automated systems. This new role requires active engagement with artificial intelligence tools. Hence, staying updated with artificial intelligence techniques is crucial for professional accountants. This involves embracing automation, adopting advanced accounting software, and understanding how artificial intelligence impacts their field. (Güney, 2014; Kairos, 2016).

Because of the vast advancements in data availability and modeling methodologies, as well as the notable rise in the application of automation, software, and emerging technologies in the accounting industry. These technologies can help accountants determine patterns and anomalies in big data, as well as forecast future trends depending on historical data, enabling stakeholders to anticipate potential risks, additionally make decisions more informed (Chowdhury, 2023). According to Zemankova (2019), artificial intelligence tools have different influences on the main outputs of accounting systems, represented by accounting information. On the one hand, artificial intelligence has an adverse influence on the importance of accounting information in today's highly technological business environment. because of their high capacity to analyze and evaluate big data sets accurately, offer insightful analysis of past trends, and even generate significant future forecasts about the future of companies, compared with accounting systems.

On the other hand, integrating artificial intelligence tools with accounting systems can enhance the productivity and capabilities of accountants. Automating repetitive tasks allows accountants to concentrate on intricate and valuable work by automating repetitive procedures that would otherwise take much time and involve rules. As a result, there are fewer mistakes in financial statements, which become more transparent and relevant, and stakeholders' confidence in accounting information increases (Zemankova, 2019; Qasaimeh et al., 2022). **Therefore, the researcher concludes that using artificial intelligence tools allows accounting information to**

be performed more accurately and with fewer errors. This improves the reliability and relevance of accounting information in the technology-driven business environment.

Machine learning (ML) is the tool of artificial intelligence that automates analytical model building and involves a combination of algorithms and statistical models (Jin et al.,2023). These models employed an iterative approach to learn-self automatically and continuously from the time series of historical data to increase stakeholders' ability to understand, identify, and extract patterns and inferences to learn from given data to make predictions and adapt to new inputs without explicit programming (Kelleher & Tierney, 2018). Therefore, ML algorithms are adequate for approaching a wide set of issues that include Classification, Cluster Analysis, and Linear Regression (Ucoglu, 2021). In this way, ML algorithms make it possible to extract insights from massive sets of accounting information. Consequently, using this tool increases the ability to produce more accurate and consistent measurements, which yield more accurate predictions (Barboza, et al., 2017). Despite the advantages of machine learning algorithms in accounting systems, they have their downsides. With the increased accuracy of financial predictions using machine learning algorithms, these algorithms will likely replace accounting systems. This, in turn, leads to the creation of uncertainty and anxiety within the accounting industry. However, there are still some accounting practices that these algorithms cannot do, like accountants. There are also ethical problems concerning the risk of bias and logical errors, potential security risks, and violating privacy regulations in the algorithm design, so these algorithms cannot fully replace accounting systems in all aspects (Alarcon et al., 2019; Ucoglu, 2021; Jin et al., 2023).

2. Research problem:

Because of the importance of accounting information's predictive ability, many attempts have been made to improve its accuracy. One of the issues with accounting systems is that, in general, ML models outperform traditional prediction models that rely on accounting information in terms of financial prediction accuracy (Easton et al., 2021). In the same context, recent studies (Zemankova, 2019; Qasaimeh et al., 2022) have determined that using advanced models based on ML algorithms instead of traditional models relying on accounting information will improve the accuracy of accounting information' predictive ability. This implies that intelligent statistical learning techniques, including ML, may provide a viable methodological catalyst to improve the predictive ability of prediction models.

In this study, the researcher examines the ability of models that rely on ML algorithms to determine predictive variables compared to models that rely on accounting information. It is expected that ML algorithms will influence the role of accounting information in financial predictions in three main ways. First, it potentially replaces accounting information in specific tasks. Second, they are expected to support existing accounting practices by improving work efficiency and, in turn, support the role of accounting information. Finally, it is expected that ML algorithms will act as business partners with accounting systems and improve the predictive ability of accounting information. The most effective work approach combines accountants and ML. According to the Swedish Institute of the Accountancy Profession, accounting information can play new and value-added roles nowadays with artificial intelligence technologies, specifically with the integration of ML algorithms in the accounting industry.

It is expected that accounting roles in modern business environments will change shortly, in this viewpoint, there is a question raised about how the impact of ML algorithms on accounting information' predictive ability will be. Moreover, to explain this relationship in the Egyptian Accounting Practice Environment by investigating whether machine learning algorithms are replacing accounting information in predictions of stock prices. Which one has more predictive ability in financial predictions, representing the prediction of cash holding? Finally, the examination of whether combining accounting information with machine learning algorithms can lead to more accurate prediction performance, representing the prediction of cash holding. **Therefore, the research problem can be expressed in how to answer the following questions practically**: Do machine learning algorithms replace accounting information as input in financial prediction models, represented by stock price predictions for Telecom Egypt company? Do machine learning algorithms have more predictive ability than accounting information in predicting cash holdings for Egyptian non-financial listed firms? Does integration between machine learning algorithms and accounting information improve the accuracy of the prediction models of cash holdings for Egyptian non-financial listed Firms?

3. Research Objective:

The purpose of this study is to test how ML algorithms influence the accounting information' predictive ability for Egyptian listed firms. Several sub-objectives are derived from this objective. **Firstly**, address and test whether ML algorithms will replace traditional prediction models based on accounting information in financial predictions by comparing the accuracy of stock price predictions made using advanced ML algorithms models to traditional prediction models that rely on accounting information. **Secondly**, test and evaluate if ML algorithms can predict cash holdings more accurately than accounting information. **Thirdly**, test the influence integration between ML algorithms and accounting information on accurately predicting cash holding, compared to exhibited by each model separately. To fulfill this study's expected objectives, the researcher used several approaches such as case study approach, event study approach, and empirical study for a sample of Egyptian non-financial listed firms from 2019 to 2022.

4. Research Importance:

The practical importance of this study stems from the emergence of one of the most crucial challenges facing accountants in the era of ML algorithms and their influence on the accounting information' predictive ability. The current study is important because it applies to one of the largest and oldest telecommunications companies in Egypt and the Middle East, Telecom Egypt Company. This company is the first Egyptian company to rely on advanced technology to perform its work. Additionally, this research compares the accuracy of traditional accounting models and machine learning algorithms in the prediction process in a business environment to develop a new accounting prediction model by combining machine learning algorithms and financial statement information from Egyptian listed firms. This comes considering the growing interest in ML algorithms in the Egyptian accounting practice environment, which may have implications for the accuracy of the predictive ability of accounting information. **Lastly, the academic importance of this study** stems from its contribution to bridging the theoretical, as well as practice research gap in two facets: first, it adds to the stream of prior literature in the era of ML algorithms in the accounting field as it investigates the influence of ML algorithms in improving accounting information' predictive ability through time savings and accuracy in accounting estimates. Second, with machine learning algorithm algorithms, this research has documented empirical evidence on the impact of ML algorithms on accounting information' predictive ability.

5. Research limitations:

This study is limited to examining the impact of ML algorithms in improving the predictive ability of accounting information only, regardless of the other qualitative characteristics of useful accounting information, such as Faithful Representation, Comparability, Verifiability, Timeliness, and Understandability, which are not in the scope of the current study. On the other side, the study is limited to comparing the prediction of stock prices and cash holding using traditional prediction models that rely on accounting information and advanced ML models, which is part of artificial intelligence, regardless of using other new methods and aspects of data analytics and artificial intelligence models, such as deep learning and data mining which is not in the scope of the research. Also, using ML algorithms in fraud detection, taxes, and accounting estimates is outside the scope of this research. The research is also limited to four ML algorithms including K-nearest neighbors (KNN), support vector regression (SVR), decision trees (DT), as well as multiple linear regression (MLR), regardless of the other algorithms, such as k-means. Regarding the geographical limitation, this study is limited to studying a sample from Egyptian non-financial listed firms regardless of the financial and unlisted Firms. Regarding the time limitation, the study is limited to the period from 2019 to 2022. Finally, the generalization of the study results will be conditional on these limits, the controls on the selection of the study's population and sample, the study's period, the statistical tools used to test the hypotheses, and the methods of measuring variables.

To fulfill the research objectives and answer its questions, the rest of the research will be structured as follows: **Section 6**: The theoretical framework and hypothesis development are covered in Section 6, which also includes an overview of ML algorithms, the predictive ability of accounting information, an analysis of previous research on these topics, and the development of research hypotheses**. Section 7:** Research methodology. **Section 8**: Analyze an empirical results. **Section 9**: Concludes, presents the research recommendations, and provides future research.

6. Theoretical Framework and Hypothesis Development

This section is divided into three subsections. The first section provides an overview of machine learning algorithms. The second section discusses accounting information's predictive ability. The third section analyzes the relationship between machine learning algorithms and accounting information’s predictive ability and develops hypotheses.

6.1 The Predictive ability of accounting information:

Financial reports are one of the stakeholders' main information sources. These reports should be prepared according to a conceptual framework for financial reporting to be valuable for stakeholders. Accounting information is valuable when it is relevant and faithfully representative (IASB, 2018). The relevance of accounting information means that accounting information influences stakeholders' decisions regarding stock prices (Imhanzenobe, 2022). According to IASB (2018), Relevant accounting information has a confirmatory and predictive value. Confirmatory value offers feedback that confirms or changes stockholders’ evaluations of past events and previous evaluations, while predictive value offers predictions related to future events (IASB, 2018). In this context, Predictive value is a qualitative characteristic that enhances the relevance of accounting information. Accounting information' relevance has predictive value if it can be used as an input into predictions models by stakeholders (IASB, 2018).

Predictive ability is defined as the process through which one predicts what will happen in the future of a phenomenon based on the behavior of this phenomenon in the past period using one of the prediction models (Farhood, 2019). Thus, the predictive ability of accounting information refers to the ability of this information to provide insights about companies' ability to collect future liquidity and provide information about economic phenomena to evaluate the income placed by capital providers Money in a way that helps them form their expectations and hopes for the future (Al-Hijjawi & Al-Ubaidi, 2015).

According to this definition, accounting information improves the ability of stakeholders to make their future expectations based on historical and current events. Therefore, accounting information must be characterized by its ability to predict future events to increase stakeholders' confidence in it. The predictive ability of accounting information does not mean that the accounting numbers are predictions about future events' results. Rather, they can be relied upon to make financial predictions about future economic decisions. Accounting information must not be predicted or forecasted to have predictive value (Chang et al., 2024). **The researcher concludes from this discussion** that the predictive ability of accounting information is one of the qualitative characteristics of relevant accounting information, which help users predict the returns associated with future activity based on analysis of the results of events in the past period.

Talkhan (2017) indicated that accounting information plays two fundamental roles in financial markets: The evaluative role and the contractual role. **The evaluative role**, accounting information helps stakeholders evaluate the company's performance and make less biased expectations about its future performance and future cash flows. This role is achieved by providing relevant accounting information that helps stakeholders estimate risks, timing, and uncertainty related to their future economic decisions. Therefore, this role focuses on how accounting information can help improve stakeholders' ability to predict future events and returns. The evaluative role also assumes that stock prices implicitly reflect a company's true financial performance by incorporating accounting information available to financial market participants into their investment decisions. For accounting information to fulfill its evaluative role, it should be prepared in accordance with accounting standards and the conceptual framework for preparing financial reports to be useful for stockholders.

Also, Talkhan (2017) showed many approaches to evaluating and measuring the relevance of accounting information, such as the predictive approach, the informative approach, and the fundamental analysis approach. **The predictive approach** states that accounting information is considered appropriate if it includes variables used in forecasting models as inputs or helps predict those variables. Therefore, the relevance of accounting information can be measured based on its ability to predict future distributions, profits, or cash flows. **According to the informative approach**, the relevance of accounting information is measured by determining the range of its ability to meet investors' expectations in the financial markets, which in turn leads to a change in stock prices. as the market reaction to the accounting information disclosed in the financial statements is tested using an event study based on the earnings response factor. According to **the fundamental analysis approach**, the relevance of accounting information is evaluated based on its ability to predict future accounting profits, especially when preparing financial statements based on accrual accounting. Additionally, this approach suggested that accounting information causes a change in the direction of stock prices in financial markets. The relevance of accounting information is inferred by measuring the abnormal returns resulting from exchange operations (buying and selling) based on accounting information. Therefore, investors can achieve extraordinary returns through accounting information available to participants in financial markets.

More precisely, investors prefer that financial reports provide information relevant to companies' financial performance valuation. The usefulness of accounting information for equity valuation is measured through value relevance models (Bath et al., 2001). Thus, predictive ability can be viewed as a measure of accounting information usefulness from investors' perspective (Beisland, 2009). The predictive value can be assessed by the statistical association between accounting information and stock prices. The stock price refers to the current value of future cash flow/earnings. So, the predictive ability of accounting information from the perspective of investors can be indirectly assessed by evaluating the ability of accounting information to predict future cash flow and earnings, which are drivers of company value (Beisland, 2011). from the modern valuation theory perspective, accounting earnings are the price driver of company stock, not cash flow. So, prediction models focus on accounting earnings instead of cash flow discounting when using the residual income model or the abnormal earnings growth model to predict earnings and cash flows based on accounting information (Penman, 2009).

Several prediction models, such as those used for forecasting stock prices and cash holdings, employ accounting information as an input. Yang (2016) demonstrated that stock price prediction involves both fundamental and technical analysis. Fundamental analysis estimates the intrinsic value of a stock by evaluating various internal and external factors of a company through content analysis of financial and other relevant reports. This approach is grounded in the efficient market hypothesis, which asserts that "information influencing a company's value is accurately and promptly reflected in the stock price." Therefore, it predicts stock price movements rely on the assumption that the stock price reflects the intrinsic value of the stock.

Technical analysis is an approach used to identify patterns in stock price movements, which can then be used to forecast future stock prices. in contrast to fundamental analysis, which considers the intrinsic value of a stock, and technical analysis relies on historical data, such as past stock prices and trading volumes, to make predictions. This method, often referred to as the chartist's approach utilizes charts for analysis (Yang, 2016). Various prediction models have been developed to predict stock prices using companies' financial statements, including the Ou and Penman model (1989), the Holthausen and Larcker model (1992), and the Fama model (1992). There are numerous debates regarding the reliability of the previous prediction models, as a result, increased dependence on mathematical, analytics, statistical, and soft computing techniques in Predictive modeling, is very popular in predicting the stock price using past events in past periods (Adebiyi et al., 2014). Despite being popular in making predictions, this model has some limitations, such as seasonality, non-stationarity, and other factors (Islam & Nguyen, 2020).

This study aims to predict the stock price by analyzing accounting information disclosed in financial statements *related* to economic events in past periods. So, Predictive modeling is more model suitable for achieving this objective

Regarding cash-holding prediction, Donepudi, et al. (2020) explain that cash-holding predictions are essential for determining the optimal cash holding level in the future. And assist managers in determining how the cash can be used to generate more profit and how managers can protect the company from financial challenges. Studies have employed several financial ratios at the firm level to predict companies' cash holdings by using traditional regression models. Some models used size, leverage, dividend, sales growth, net working capital, cash flow, and capital expenditure in cash-holding prediction models.

Based on this discussion, The researcher concluded that accounting information has predictive ability if it can used as an input in prediction models or assists in predicting these models′ variables. In this context, this study focuses on two prediction models based on accounting information, the stock prices prediction model and the cash holding prediction model, to investigate the predictive ability of accounting information

6.2 Overview of Machine Learning Algorithms.

While the terms "Artificial intelligence" and "machine learning (ML)" are sometimes synonyms for each other, they have distinct meanings (Zemankova, 2019). ML is an artificial intelligence tool that uses advanced algorithms trained on datasets to build models that allow machines to carry out tasks and replicate cognitive functions that are otherwise only possible for humans like learning, problem-solving, classifying images, analyzing data, or predicting price fluctuations(Fadaly & Gohar, 2023). ML algorithms have applications in various areas related to accounting systems, including fraud detection, auditing, distress prediction, credit ratings, accounting estimates, and financial prediction (Chen et al., 2022). **So, this section will highlight the ML algorithms concept and its phases.**

About its definition, Russell et al. (2018) define ML algorithms as "the ability to use techniques that allow computers to learn and improve without being programmed". These algorithms are advanced technologies that can learn to recognize patterns, which enables them to make accurate predictions. In other meaning, ML is dynamic and continuous process that uses algorithms, which are sets of guidelines that have been adjusted and refined based on historical datasets, to predict and classify new data based on the differentiating characteristics learned from historical datasets (Singh et al., 2023). These algorithms are not static and need to be refined several times to build a comprehensive set of instructions that let them operate effectively (Ding et al., 2020). This continuous learning aspect is not just a feature but a defining characteristic that keeps machine learning engaging and constantly evolving. It ensures that professionals are always part of a dynamic and changing field where new challenges and opportunities arise (Easton et al., 2021; You & Cao, 2021). Consequently, ML models are simply algorithms that have been designed and trained sufficiently to perform certain tasks such as predicting stock prices or making decisions. As a result, despite the essential principles of ML learning algorithms being relatively straightforward, the generating models may become highly complex by the end of the training process. (Browen, 2021).

Applied this in accounting systems means dealing with large volumes of data and their flow speed as they are collected and processed immediately. This leads to automated, tedious, and repetitive work; streamlining tasks and reducing workload are promising aspects for professionals in the field. As well as saving time, reducing costs, and increasing productivity, which allows professionals accountants to focus on more complex and value-adding tasks (Brennan et al., 2017; Zemankova, 2019; Lee & Tajudeen, 2020; Stancu & Dutescu, 2021; Jin et al., 2023).

The researcher concluded that ML algorithms have the potential to streamline tasks and reduce workload in accounting systems. By dealing with large volumes of data and automating tedious work, they can save time, reduce costs, and increase productivity. Machine learning uses dynamic algorithms that learn from historical data to make predictions and categorize new data. The continuous process results in complex ML models that perform specific tasks such as predicting stock prices and decision-making.

Regarding the ML algorithms phases, Banoula (2023) explains that the ML process consists of a series of phases, as shown in Figure (1). First, **the data collection phase** includes obtaining raw data from several sources. This data is then arranged and prepared to serve as training data—that is, the data that the computer learns from. Second, **the data preparation phase** involves cleaning data, error removal, and formatting it in a way that computers can understand. It also includes feature engineering—also referred to as feature extraction—which involves selecting relevant patterns to assist the computer in completing certain tasks. To ensure that the training data is adequately diversified and representative of the problem sufficiently, engineers must employ huge datasets.

Selecting and training the model is the third phase. Selecting a suitable ML model and training procedures relies on that certain task. The model acts as an assistant tool that aids the computer in interpreting the data. During the training phase, the computer model automatically gains knowledge from the data by looking for patterns and modifying its internal parameters. It essentially teaches itself to identify connections between patterns to predict future events based on the patterns it finds. **Model optimization is the fourth phase**. In this phase, the accuracy of the model may be increased by human specialists by modifying any of its settings or parameters. To improve the model′s ability to generate accurately predictions or identify significant patterns within the data, programmers test out several configurations (Banoula, 2023). **The fifth phase is the model evaluation phase**. After the training phase, the model needs to assess its performance using separate data added to the model after excluding the training data. in this phase, testing the model's ability how well it can generalize its learnings from training data. Also, assessing the model's ability to provide insights for further improvements**. The final phase is the model deployment phase**. Once the model has been trained and evaluated, it is put into use to make predictions or identify patterns in new unobserved data. And the model continues to adjust automatically to improve its performance over time (Banoula, **2023).**

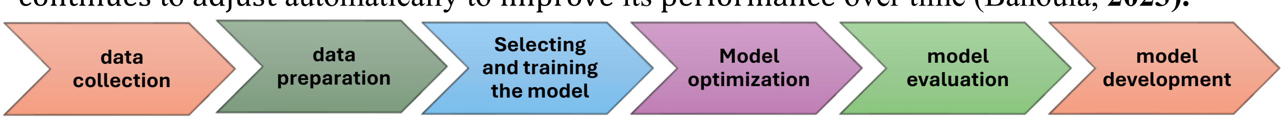

Figure (1): Phases of machine learning
Source: the researcher

ML involves a variety of algorithms, like Supervised algorithms, Semi-Supervised algorithms, Unsupervised algorithms, and Reinforcement Learning algorithms, as shown in Figure (2). **Supervised learning algorithms** are represented in Nearest Neighbor Algorithms (NN), Naïve Bayes Algorithms (NB), Bayesian Belief Networks (BBN), Decision Trees (DT), Random Forests(RF), Linear and Logistic Regression(LR), Neural Networks(NN-k), Deep Learning(DL), and Support Vector Machines (SV) (Lantz,2015). These algorithms are utilized with datasets that contain trained and labeled data sets along with target information, allowing them to learn and grow more accurate in interpreting each piece of data over time. meaning there are input data points with known corresponding outputs (Castle, 2017). Consequently, supervised learning algorithms are suitable for prediction and classification purposes based on historical data, like determining which customers are most likely to default on their debt (bankrupt and non-bankrupt) (Browen, 2021). **Unsupervised learning algorithms** include Association Rules, Clustering (ARC), and Unsupervised Neural Networks (UNN_K) (Lantz,2015). These algorithms are utilized when there are unlabeled data sets without tags, requiring algorithms to uncover patterns independently (Castle, 2017). According to this method, the system is not provided with the assumed answers, but it can discover patterns or trends within the data autonomously that people aren't explicitly looking for. Unsupervised learning algorithms involve various techniques that can be applied to transactional data, such as cluster analysis, and can be beneficial if used as part of the risk assessment process to discover previously unforeseen risks.

In context, **semi-supervised algorithms**, algorithms are trained using labeled and unlabeled datasets. Where algorithms are initially fed a small amount of labeled data to guide their development, followed by huge quantities of unlabeled data to complete the model. This method is commonly used for classification and prediction tasks when labeled data are scarce (Lantz,2015). In contrast, algorithms are trained via the rial-and-error method in **reinforcement learning algorithms.** Where these algorithms operate within specific environments and receive feedback after every outcome. This method allows algorithms to learn from past successes and failures by indicating to the machine when they make the correct decisions, gradually helping the machine determine the appropriate actions to take. In summary, ML is a multifaceted process that enables the creation of machines and applications capable for operating without human supervision (Browen, 2021). **In light of the current study problem and its objectives, the researcher will depend on Supervised learning algorithms to predict stock prices and cash holding based on historical data**

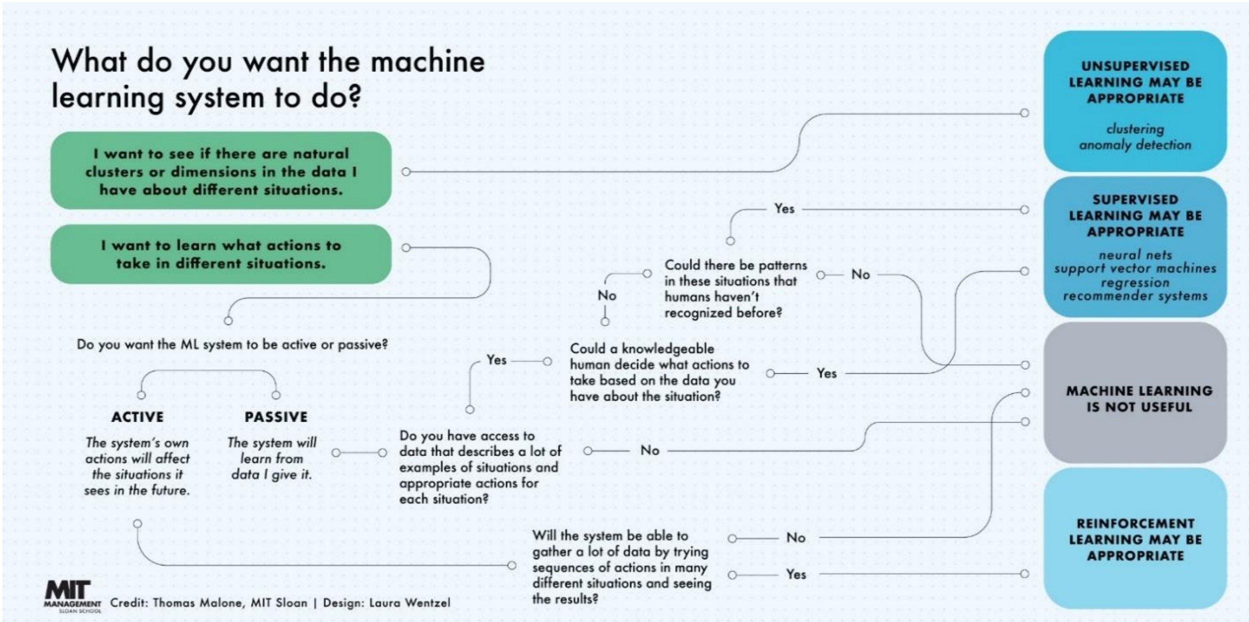

Figure (2): Forms of machine learning

Source: Browen, 2021

Several benefits lie behind applying ML algorithms in a business environment. These benefits involve reducing overall operational costs by helping professionals automate some of their jobs. ML algorithms also improve operational efficiency and accuracy by executing specific tasks with precision, ensuring timely completion to a high standard (Lee & Tajudeen, 2020). Moreover, ML algorithms improve insights by quickly identifying trends and patterns in big datasets, a process that would be time-consuming for humans (Brennan et al., 2017). Additionally, ML algorithms support decision-making by processing and analysing massive amounts of data and identifying hidden trends and relationships. This empowers decision-makers with actionable insights, allowing for strategic planning and more precise resource allocation. Also, machine learning models, through robust predictive analytics, contribute significantly to risk mitigation by foreseeing potential challenges and identifying areas of concern; organizations can proactively implement measures to minimize risks and protect their interests (Lee & Tajudeen, 2020; Jin et al., 2023).

Despite their unique advantages, machine learning algorithms have their downsides. On the one hand, labor unemployment is increasing since certain professions are being automated, and these machines are replacing entry-level or low-level employees. This, in turn, leads to rising unemployment among humans and the creation of uncertainty and anxiety within the different industries. Employees in the affected industries may also suffer layoffs that require them to change careers or put them at risk of long-term unemployment (Ding et al., 2020). at the same time, the absence of the human element can be a downside, as models designed to perform specific tasks may fail to capture many of the important human factors that are essential to the successful completion of those tasks (Alarcon et al., 2019).

Bias problems are another significant concern about ML algorithm applications, as there is a risk of bias and logical errors in the model design. Just like the humans who create them, ML *models* can exhibit bias from the datasets they are trained on by humans. If these datasets are skewed or reflect existing inequalities, the models will learn to replicate and perpetuate these biases (Alarcon et al., 2019). Furthermore, there are potential security risks and privacy violations associated with ML applications, which must also be carefully considered (Ucoglu, 2021; Jin et al., 2023).

6.3 Machine learning Algorithms from an Accounting perspective:

According to professional bodies, (SSF, 2019; AIPCA, 2022; PWC, 2021), most accounting professionals expect artificial intelligence to grow in the accounting industry over the next years. Hence, many accounting tasks face the risk of being replaced by machines shortly due to automated accounting processes such as Invoice processing, Fraud Detection, Financial analysis, Future Predictions, Tax Compliance and Preparation, Bookkeeping and Entering Data, and supporting Auditing. As a result, in 2016, the Big Four accounting firms announced the use of financial robots in their daily work of accounting and began adopting these robots to replace financial accountants. These firms have been progressively embracing technological advancements, particularly AI, to leverage its capabilities in doing repetitive daily tasks in accounting, auditing, and taxation. This shift compels accountants to enhance their skills to adapt to the gradual digital transformation in the accounting industry. More importantly, these challenges drive the accounting profession to continuously develop to keep pace with the evolving business environment in the era of machine learning algorithms (Zemankova, 2019; Ucoglu, 2021; Jin et al., 2023).

In this context, many accounting research explained that using ML Algorithms in accounting practices helps accomplish several tasks, such as detecting fraud or other financial misstatements in financial statements to improve the quality of accounting information (Cecchini et al., 2010). As well as ML Algorithms can be used by accountants to substantially improve the accuracy of their accounting estimates used in preparing financial statements, which in turn influences the relevance of accounting information (Ding et al., 2020). Also, ML Algorithms can be used in generating forecasts of future earnings, cash flow, and stock prices using firm characteristics that are incrementally informative in forecasts of future cash flow, stocks, and earnings. Moreover, ML algorithms are used to evaluate and manage risk dimensions. (Monahan, 2018; Anand et al., 2019; Browen et al., 2021).

Florackis et al. (2020) have proven that the application of ML algorithms are useful in predicting future cyberattacks and managing cybersecurity risks effectively. In the same context, Donvan et al. (2021) showed that the use of ML algorithms to develop a comprehensive measure of credit risk based on data disclosed in financial statements improves the accountants′ ability to predict credit events, such as bankruptcy, interest spreads, and credit rating downgrades, more effectively than other credit risk measures. Furthermore, ML Algorithms may be useful in processing accounting information to predict stock prices. By analyzing the relationship between a firm's stock prices one year ahead and the accounting information from the previous four years for the firm and *its* industry. Consequently, these algorithms provide valuable insights cuseful in financial predictions (Chen et al., 2022; Van Binsbergen et al., 2022; Binz et al., 2023).

Concerning the impact of ML algorithms on accounting information, several accounting researchers, such as (Stancheva-Todorova, 2018; Qasim & Kharbat, 2020; Lee & Tajudeen, 2020; Ardichvili, 2022; Fadaly & Gohar, 2023) discussed the advantages and disadvantages of the application of ML algorithms in accounting systems. One of the most important advantages of ML algorithms are that they automate routine tasks, like data entry, freeing up accountants' time to focus on more complex tasks that require human expertise, leading to an increase in productivity, improved efficiency, and support the flexible working style, along with an increase in effective governance, saved manpower, saving time, and reduced costs by using budgeting and forecasting software, to create precise and trustworthy financial projections that may be used to enhance strategic decision making by analyzing financial data. Real-time insights into a company's financial performance may also be provided by machine learning, allowing accountants to see possible dangers and opportunities early on (Stancheva-Todorova, 2018).

Incorporating ML algorithms into accounting systems allows for the analysis of huge of financial data with a high level of accuracy and speed that surpasses humans capabilities. This significantly reduces the likelihood of errors, ensuring that financial statements are accurate and reliable. Moreover, ML algorithms can identify patterns and trends in financial data that may be difficult for accountants to detect (Binz et al., 2023). Doing that helps accountants overcome the limitations faced by traditional accounting systems, improving efficiency and accuracy, which leads to improved financial performance and ultimately supports better decision-making processes. The improved accuracy and reduced errors provided by ML algorithms also can help accountants improve the efficiency of their operations. For instance, using ML algorithms-based accounting systems in accounting processes like accounts payable and receivable can streamline these processes, ensuring timely payments to suppliers and fostering trust (Deloitte, 2015).

Furthermore, ML algorithms play a crucial role in analyzing financial data to identify tax credits and deductions, which helps firms reduce their tax liabilities. It also detects misstatements or omissions in tax files to ensure compliance with regulations and maximize tax savings (Ardichvili, 2022). Also, accounting transactions, Recordkeeping, and bookkeeping can be classified by ML algorithms to maintain accurate financial records, though it still requires the guidance of human expertise (Qasim & Kharbat, 2020). Fadaly and Gohar (2023) have proven that ML algorithms significantly affect the efficiency with which accounting tasks are carried out in accounting firms. It was found that the efficiency of accounting procedures is increased by the application of ML algorithms. In this regard, Stancu and Dutescu (2021) provided evidence that accountants are already integrating advanced technology into their daily work to enhance the efficiency of their performance and save time. So, in the accounting industry, implementing machine learning is not an unfamiliar idea, and implementation gives significant benefits, including the ability to make data-driven decisions to achieve target objectives, the use of accounting data analytics to gain insights into business performance, and the significant time savings resulting from the elimination of repetitive tasks. (Sutton et al., 2016).

On the other hand, ML algorithms bring along their own set of challenges. One of the primary drawbacks of incorporating ML algorithms into accounting is the high initial implementation costs. According to Deloitte's report (2022), these costs may exceed millions of dollars contingent upon the firm size and complexity of their processes. This involves the cost of procuring hardware and software, training accountants, and maintaining and upgrading systems continually (Deloitte, 2022). There are also challenges with the potential for job displacement. Moreover, there are challenges related to the potential for accountants' job displacement. As ML algorithms automate several accounting tasks, there is a possibility that some accountants may lose their jobs, a concern echoed by numerous experts in the accounting domain (Jin, et al., 2023). Consequently, accountants must overcome these challenges by adapting with the requisite skills and knowledge in the age of artificial intelligence, where it's become crucial for accountants to continually enhance their skills to bridge the gap in the availability of accounting professionals proficient in both accounting and ML algorithms. This may involve upskilling existing employees, hiring new talent with expertise in artificial intelligence and data science, or partnering with external consultants who can provide support (Fadaly and Gohar, 2023).

In the same context, Soltoggio et al. (2024) stated that Several risks arise from the application of ML algorithms such as security risks and misinterpretation risks. Security risks arise from the incompatibility of traditional accounting system structures with new ML techniques. This leads to creating data silos where important data remains stored within the traditional systems, limiting ML algorithms' ability to access and analyze data effectively. Misinterpretation risk is represented in the potential that people will misunderstand the insights produced by ML algorithms, leading to incorrect decisions. Such misinterpretations can occur due to biased data inputs, erroneous algorithms, or insufficient human oversight (Alarcon et al., 2019). Furthermore, many accounting professionals might not completely understand the capabilities and limitations of ML algorithms as artificial intelligence tools because it is still a relatively new technology (Ranta, et al., 2023).

Based on the preceding discussion, the researcher can conclude that ML algorithms are relatively new AI tools that are quickly growing across the accounting industry. Over time, the benefits of these algorithms in the accounting and finance field have become increasingly evident. for instance, ML algorithms can detect intricate patterns and correlations within financial data and process a large volume of both structured and unstructured data. This capability significantly shortens the data processing cycle, thereby improving the efficiency and effectiveness of accounting treatments, reducing errors, and increasing the relevance of accounting information. To summarize, ML algorithms have completely revolutionized accounting processes, particularly those that provide stakeholders with more accurate predictions. As a result, accounting researchers and practitioners regard ML algorithms as valuable tools for making financial predictions**.**

6.4 Analysis of Machine Learning Algorithms' Role in Improving the Predictive Ability of Accounting Information and Hypotheses Development

Based on the results of Sutton et al. (2016), it is clear that there is a growing trend of using ML algorithms instead of accountants in accounting tasks. This has increased the questions around the role of ML algorithms in the accounting industry and its impact on accountants' role (Shimamoto, 2018). A study by Lee and Tajudeen (2020) has confirmed that 95 percent of the accountants interviewed experienced a concern of losing their jobs in the future because of increasing the role of ML algorithms in accounting processes by enhancing the accuracy and reliability of accounting systems outcomes. As well as this study also found that ML algorithms can directly improve accounting estimates by revealing the mechanisms through which they may alleviate both intentional and unintentional errors in accounting estimates. This led to improving the quality of accounting information and enhancing the usefulness of financial reports to stakeholders (Ding et al., 2020). In the same context, the study by Bertomeu et al.

(2021) indicated that ML algorithms offer new ways to find patterns in accounting numbers and help regulators monitor reporting practices.

Concerning the impact of ML algorithms on the role of accounting information, Brennan et al. (2017) refer to financial robots that enhance the efficiency of accounting systems by utilizing AL technology to perform most of the accounting processes. The results of this study showed that the introduction of financial robots in accounting systems not only reduces labor costs but also improves the accuracy, reliability, and predictive ability of financial data, effectively solving problems like estimation errors compared to traditional accounting methods. Additionally, financial robots can seamlessly transfer data between platforms, conduct data reconstruction and analysis, and effectively handle tasks related to information monitoring and processing. (Trigger et al., 2018).

Consistent with that, Zemankova (2019) suggested that ML algorithms can easily automate routine accounting tasks like bookkeeping, tax declaration, accounts receivable and payable management, preparation of expense reports, and risk assessment, which in turn leads to improved quality of accounting information. Similarly, Breheney (2023) indicated that several repetitive tasks performed by accountants, including data extraction, processing, comparison, and verification, can be efficiently managed by ML algorithms. This would allow for automatic recording, classification, and analysis of financial transactions within the accounting system. Consequently, ML algorithms have the potential to significantly improve the accuracy and efficiency of accounting systems, reduce costs for accounting, and free up accountants' time to concentrate on higher-level, value-added tasks. However, applications of ML algorithms also lead to the risk of diminishing the accountant's role within the accounting industry (Jin, et al., 2023).

Based on the discussion above, the researcher concludes that ML algorithms have the potential to revolutionize the accounting industry by improving the accuracy, reliability, and integrity of financial statements, as well as effectively addressing issues such as estimation errors. More significantly, machine learning algorithms can take over various accounting tasks by automating repetitive and time-consuming activities such as data identification, extraction, processing, comparison, and verification. Additionally, they can automate tasks like the classification and analysis of financial transactions, bookkeeping, tax declarations, accounts receivable and payable management, expense report preparation, and risk assessment. This automation allows accountants to focus more on tasks that require higher levels of professional judgment, thereby elevating the overall value of their work, on the one hand. On the other hand, this automation allows ML algorithms to replace accountants in several accounting tasks.

In advanced research, Deng (2018) developed a specialized ML algorithm called the InTrees algorithm to improve the predictive accuracy of accounting variables by integrating them with market variables to provide a more dynamic perspective of the influence of ML algorithms on accounting information. The InTrees algorithm relies on the gradient-boosted regression tree (GBRT) ensemble learning model. The InTrees algorithm extracts simplified rules from GBRT by setting thresholds that make the model's predictions more interpretable. This approach illustrates the potential of ML algorithms, particularly the InTrees algorithm, in improving financial predictions by integrating multiple sources of data.

Using the InTrees algorithm, Deng (2018) emphasized that there is an intuitive integrative Relationship between market variables and accounting information in financial predictions. Market variables can complement accounting information, which may be incomplete or biased due to accounting rules or managerial discretion. market variables can partially fill this gap and consider internally generated assets and probabilistic variables that are not disclosure in the financial statements and events that influence the firm more immediately.

Similarly, Bertomeu et al. (2021) added that ML algorithms offer an empirical approach for analyzing accounting information in conjunction with numerous market variables. These algorithms are instrumental in identifying and interpreting complex patterns associated with repeated accounting misstatements and illustrate the links between those patterns and transactions. The study utilized numerous of variables like accounting, capital markets, governance, and auditing datasets to detect material accounting misstatements. One of the key findings of the study is that introducing ML algorithms in accounting procedures makes it easier for accountants to analyze huge databases of account transactions. where ML algorithms offer a high-level summary of all the activities carried out, this approach enables accountants to detect ongoing accounting misstatements efficiently.

To gain a more interactive view of the influence of machine learning algorithms on accounting information, (Ardichvili, 2022, Jin et al., 2023) highlight the role of ML algorithms in making accurate predictions using accounting variables. For instance, ML algorithms can provide a high-level summary of all variables, aiding in the identification and interpretation of complex patterns in ongoing accounting misstatements and revealing the connections between these patterns and specific transactions (Ardichvili, 2022). These algorithms allow vast amounts of transaction data to be quickly filtered and aggregated, enabling accountants to quickly identify patterns or relationships that might otherwise be difficult to detect. ML algorithms excel at managing and summarizing large and expanding accounting data sources, selecting the most relevant accounting variables to explain outcomes, and discovering optimal combinations of variables to make accurate predictions(Jin et al., 2023).

Concerning predictions, prior research (Ding et al., 2020; Bertomeu et al., 2021; Ucoglu, 2021; Jin et al., 2023; Fadaly & Gohar, 2023) implies that ML algorithms have the potential to significantly influence the role of accounting information in financial predictions in several aspects. Firstly, these algorithms improve the accuracy of accounting estimates by analysing huge of financial data and identifying patterns that may not be immediately apparent to analysts. This leads to more accurate accounting estimates by reducing the risk of errors or omissions. Secondly, these algorithms increase efficiency by automating many accounting tasks, like data collection and analysis, freeing up accountants' time to focus on more strategic tasks. Thirdly, these algorithms improve risk management, which helps identify potential risks and opportunities, enabling accountants to make more informed decisions about accounting estimates. Finally, machine learning algorithms can monitor and detect financial misstatements, which can help detect fraud or other financial manipulations. Overall, machine learning algorithms have the potential to revolutionize accounting estimates by improving accuracy, efficiency, risk management, decision-making, and financial predictions. ***However, it's important to note that ML algorithms are not a replacement for human expertise and judgment. Rather, it is a tool that can be used to augment and enhance the work of human accountants***.

Similarly, Ding et al. (2020) showed that ML algorithms improve accounting estimates′ predictive ability, particularly in predicting insurance payments. Analyzing insurance companies′ data on loss reserve estimates and realizations established the superiority of ML-generated estimates over actual managerial estimates reported in financial statements, with few exceptions. The finding highlights the potential of ML algorithms to independently assess the reliability of estimates underlying financial reports, ultimately improving the relevance and reliability of financial information.

In another context, Song et al. (2014) employed numerous ML algorithms to predict company bankruptcies or their default. The experimental results demonstrated that using ML algorithms decreases financial risks compared to traditional models based on accounting information by efficiently assessing financial statement fraud risk. Barboza et al.(2017) also confirm that machine learning algorithms perform better predictions than traditional accounting information models. Ding et al. (2019) designed an ML algorithm that relies on a peer-selection method that analyzes companies' financial ratios. The results indicated that this algorithm enhanced the prediction models by including information about peer companies. Furthermore, this algorithm can rank financial statements in terms of creditworthiness by detecting any anomalies in the financial statements (Lokanan & Tran, 2019).

Given the above results, the researcher concludes that these findings provide valuable insights for companies considering the adoption of ML based accounting information systems, offer evidence of their potential benefits, and serve as a guide for informed decision-making. Furthermore, prior research has argued that the power of ML can be utilized to optimize the accounting profession's role in today's dynamic business environment. So, accountants must adopt machine learning algorithms to perform their tasks and stay sustainable. Overall, adopting machine learning in the accounting profession reduces the role of traditional accountants, improves their quality, and transforms traditional accounting to meet the needs of a dynamic business environment. However, it's important to remember that machine learning is a tool, not a replacement for human expertise. While it can automate tasks and improve data processing and analysis, it still requires human oversight and interpretation. So, the researcher believes that it's become necessary for accountants to understand the limitations of machine learning and apply their professional judgment to ensure the accuracy and validity of the results. This can be achieved through continuous learning and training in machine learning-related technologies and developing soft skills such as data analysis, programming, and intelligence in business tools to navigate the challenges the machine learning environment poses.

From the perspective of the Efficient Market hypothesis, the stock price reflects all publicly available information in financial markets (Malkie, 2003). In the same context, the conceptual framework of accounting information requires that accounting information should have the ability to influence stock prices to be relevant to stakeholders (IASB, 2018). which means that accounting information plays an important role in stock prices prediction within financial markets as an input in prediction models. On the other hand, stock prices are influenced by several economic, social, political, and other environmental variables that are characterized by continuous fluctuations. So, predicting stock prices process is complex and challenging for financial analysts. Conversely, ML algorithms can identify stock trends from massive amounts of data that capture the underlying dynamics of stock prices, which prompted financial analysts to increasingly rely on these algorithms to identify the dynamics of stock price movements, and then predict stock prices. In this context, numerous studies (Dai & Zhang, 2020, Menaka et al., 2021, Mukherjee et al., 2021) have tested the accuracy of stock price predictions using ML algorithms compared to other prediction models based on accounting information. These studies have found that ML algorithm models outperform accounting information-based models in predicting stock prices. Where ML algorithms are distinguished by their ability to perform complex nonlinear analyses in multi-dimensional spaces, offering different approaches compared to other prediction models based on accounting information that rely on regression statistics.

Using a supervised learning algorithm, Dai and Zhang (2020) found that initial next-day prediction using the SVM algorithm has very low accuracy, around 50%. However, models achieved a high accuracy when trying to predict long-term stock price trends (79%). Based on this result, the stock trading strategy based on ML algorithms significantly outperforms the stock price predictions based on accounting information. Also, Mukherjee et al. (2021) designed two network models to predict stock prices; the artificial Neural Network model (ANN) and the Convolutional Neural Network (CNN) to predict daily stock prices from the last few days' data values. This process keeps repeating recursively using deep learning, leading to a great acceleration in predicting stock prices by enabling the domain expert to evaluate and comprehend predictions. The study found that the CNN model has more predictive ability than the ANN model.

Vijh et al. (2020) stated that the historical data in the company′s financial statement are insufficient to predict stock prices. So, the researchers have created new variables using ML Algorithms like the next day closing price of the stock (ANN), and Random Forest is also employed for comparative analysis to obtain higher accuracy in the predicted stock price. The comparative analysis indicates that the predictions' ability of ANN outperforms Random Forest in stock price predictions. Additionally, Results showed that the best values obtained by the ANN model are from (0.013) to (0.42). Lastly, the study recommended introducing financial parameters such as profit and loss statement elements in these models to improve the accuracy of ML models. Joshi and Chauhan (2020) evaluated determinants of stock prices and their prediction accuracy using ML algorithms compared to regression models based on financial ratios, like price to earnings (P/Es), price to book value (P/B), and price to sales (P/S). The results indicate that the implementing of ML algorithms ensures the accuracy of stock prices by minimizing errors in predictions. Furthermore, they recommended that the predictive ability of ML models is better along with fundamental analysis determinants at firm levels such as firm size, cash holding, Governance, dividend, and net profit, which influence the firm's value.

From an analysis of the results of the above literature review, the researcher concluded that these studies have emphasized that ML algorithms have the ability to predict stock prices accurately without needing to analyze accounting information, as is usually the case in traditional fundamental analysis, which influence the role of accounting information in financial predictions. Consequently, there is a trend to replace traditional prediction models based on accounting information with ML models to predict stock prices. From the viewpoint of the researcher, most of these studies examined the effect of ML algorithms on stock price prediction ignored testing the predictive ability of accounting information as a comparative approach. So, it's difficult to identify which other is better without comparative analysis. Also, most of these studies applied in developed countries, such as the US and the UK, these countries have a huge technological capacity that can use advanced artificial intelligence tools effectively compared to development like Egypt. So, the results of studies conducted in developed countries cannot be generalized to developing countries due to the difference in the level of technological progress between them. Therefore, the impact of machine learning on the role of accounting information in Egypt must be tested. **Based on the discussion above, and to fulfill the sub-first research objective, the first research hypothesis (H1) be formulated:**

Hypothesis (1): Machine learning algorithms replace accounting information in predicting stock prices for Egyptian listed firms

Cash holding prediction assist managers in determining how cash can be used to increase profit and how managers can protect the firm from financial challenges (Donepudi et al., 2020). To predict the firm's cash holdings by classical regression methods, Various accounting variables are examined at the firm level, including size, leverage, dividend, sales growth, net working capital, cash flow, capital expenditure, and tangibility (Lozano & Yaman, 2020; Diaw, 2021). On the contrary, some studies (Moubariki et al., 2019; Wu et al., 2021; Özlem & Tan, 2022; Rafi et al., 2024) attempted to predict the firms' cash holdings using ML algorithms for determining the optimal cash holding level. These studies found that ML algorithms can predict to the optimal cash holding levels algorithms instead of financial reporting and statistics accurately.

Wu et al. (2021) employed ML algorithms to *predict* cash holdings. Those algorithms include Logistic Model Tree (LMT), Random Forest (RF), REP, CHART, extra tree, and BF tree. The results showed that Random Forest had more accurate predictions than other ML algorithms. Meanwhile, Moubariki et al. (2019) analyzed cash management by applying Decision Tree, Random Forest, and neural networks. The results found that the Decision Tree outperforms other prediction algorithms for predicting cash holding. Gholamzadeh et al. (2021) added that ML algorithms along with accounting information are suitable for predicting cash holding by applying neural networks. Due to these conflicting opinions about whether ML algorithms model based on raw data can outperform the benchmark model based on financial ratios, the current study used a cash-holding prediction model that differs from the above-mentioned benchmark models in two aspects. First, it used machine learning algorithms to predict cash holdings, while most prior prediction research in accounting uses logistic regression. Second, the proposed model used raw data of financial statements, as cash holding predictors. Because raw financial data is one of the most fundamental analysis in the accounting system, it's important to explore whether it can be directly used in cash holding prediction.

The researcher concluded that the previous studies' results emphasize the potential influence of ML algorithms on the role of accounting information in cash holding predictions. Despite the consistency in the results of the accounting research in this respect, as discussed previously, there are no applied studies to test this relationship in the Egyptian business environment to the extent of the researchers' knowledge. To bridge this gap, the researcher seeks to test the impact of ML algorithms on the role of accounting information in predicting cash holding by testing the following hypothesis (2):

Hypothesis (2): Machine Learning Algorithms outperform traditional models based on accounting information in predicting cash holding.

In general, ML algorithms may influence the role of the accounting information in the business environment and the tasks of the accountants in several areas, such as supporting financial analysis predictions, and accounting estimates, and directing them to the role of business partner. Machine learning also provides the opportunity for accountants to improve their roles by saving time to focus on tasks that require more professional judgment. In this context, the researcher views ML algorithms and accounting information are partners in financial predictions, they complement each other not replacements. Accounting information must be the guiding partner, ensuring machine learning algorithms are free from bias and aligned with accounting principles. At the same time, ML algorithms have unique strengths that enable create better performance in terms of efficiency, accuracy, and progress. The results may be transformative when machine learning algorithms are integrated with accountants' professional expertise and judgments. Such integration leads to predicting financial trends with greater accuracy and uncovering hidden risks. This, in turn, leads to a deeper understanding of the financial accounting system and supporting decision-making that fosters the business environment. By embracing this trend, the accounting profession can enhance its future role concerning financial predictions. So, considering this viewpoint, the third research hypothesis (H3) be formulated

Hypothesis (3): Integrating accounting information with machine learning Algorithms as Business partners, improves predictive ability compared to that exhibited by each separately in predicting cash holding for Egyptian listed firms.

7. Research Methodology

This section Addressed the following points: the research methods, sample selection, measurement of the variables utilized in this study, and development of the research model. The researcher utilized several approaches such as case study, event study, and empirical study to investigate the role of ML algorithms in improving the predictive ability of accounting information for Egyptian listed firms.

7.1 research model

The above hypotheses are summarized in the following research model

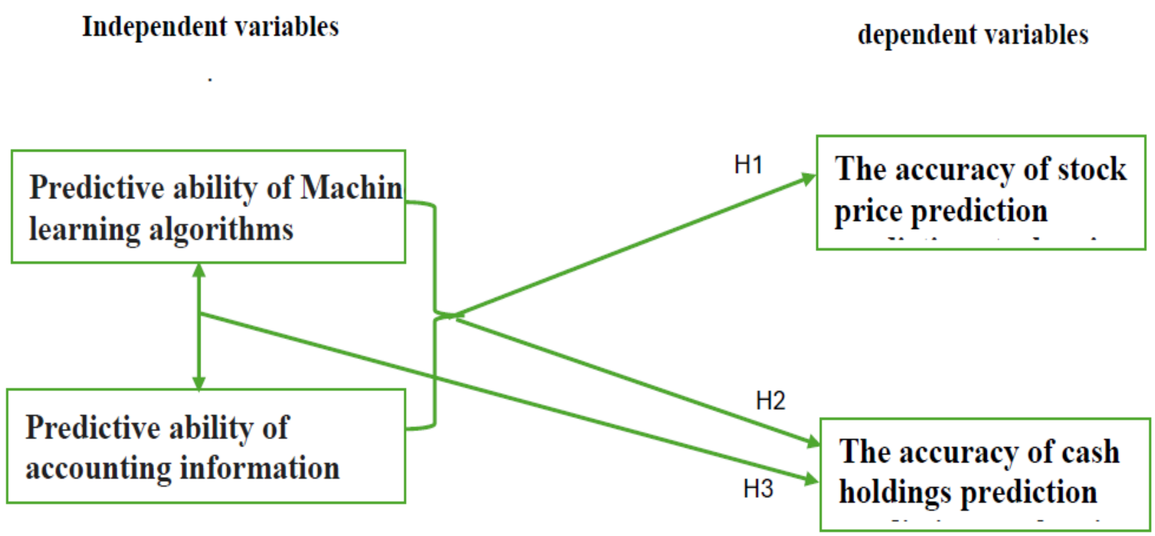

Figure 2:Research model (Developed by the

7.2 Testing and Discussion of the First Hypothesis:

For testing the first hypothesis, the researcher employed a comparative analysis method, using the Case study and Event study approaches to investigate whether ML algorithms replace accounting information in predicting stock prices for Egyptian listed firms.

7.2.1 Case Study Sample:

The case study aimed to investigate the predictive ability of ML algorithms to predict stock prices. This was applied using the Telecom Egypt stock company's daily historical stock prices during the period from 2019 to 2022. the case study approach is qualitative design enables in-depth exploration of the phenomenon, event, and process based on time and activity in its real-life context. So, it is suitable for investigating several techniques to predict stock prices based on historical and real-time stock market data. The researcher collected detailed information using a variety of data collection procedures over a sustained period. Telecom Egypt was chosen because it is one of the leading companies on the Egyptian stock Exchange, especially in technological development. This provides a greater opportunity for the availability of the longest series of times from historical data

7.2.2 Event Study Sample:

The researcher utilized the Event study approach to assess the predictive ability of accounting information to predict stock prices using multiple linear regression models by testing the impact of financial ratios and other relative accounting information on stock prices. As in the case study, the event was conducted on financial data disclosure in the Telecom Egypt company's quarterly financial reports from 2019-2022.

7.2.3 The First Hypothesis Variables:

In the first hypothesis, the researcher built two modeling techniques for predicting stock prices and compared the models' accuracy. Therefore, there are two main independent variables: the predictive ability of ML algorithms and the predictive ability of accounting information, and a major dependent variable is the accuracy of stock price prediction, which are discussed in the subsequent sections.

7.2.3.1 Dependent variable: the accuracy of stock price prediction:

In this study, the accuracy of stock price prediction is mesuered using four metrics based on (Nabipour et al., 2020; Kaur, 2021; Akhtar, et al., 2022; Erizal & Diqi, 2023) include:

1- Mean absolute error (MAE): This metric calculates the average of the absolute differences between the predicted and actual stock prices. A lower MAE indicates a more accurate model. Calculated according to Equation (1):

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \qquad (1)$$

Where y_i is the divided actual stock price on true stock price, $\hat{y}_i$ is the divided predicted stock price on forecast stock prices, and n is the total number of historical daily observations.

2- Root mean squared error (RMSE): This metric is the square root of the MSE. It is a more intuitive measure of error than the MSE, as it is in the same units as the stock price. A lower RMSE indicates a more accurate model. Calculated according to Equation (2):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \qquad (2)$$

where n, y_i , $\hat{y}_i$ is the same as Equation (1).

3- Mean absolute percentage error (MAPE): This metric calculates the average of the absolute percentage differences between the predicted and actual stock prices. A lower MAPE indicates a more accurate model. Calculated according to Equation (3):

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \frac{|y_i - \hat{y}_i|}{|y_i|} \qquad (3)$$

where n, y_i , $\hat{y}_i$ is the same as Equation (1).

4- R-squared: This metric measures how well the model explains the variation in the actual stock prices. If the R^2 value equals 1, it indicates that the model is the perfect fit, while if it equals 0, it indicates that the model does not explain any variation in the stock prices. A higher R^2 indicates a more accurate model. Calculated according to Equation (4):

$$R^2 = 1 - \frac{SSR}{SST} = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \qquad (4)$$

Where SSR is the sum squared regression (sum of the residuals squared), SST is the total sum of squares (sum of the distance the data is away from the mean all squared), $\bar{y}_i$ is the mean of the actual value ($\bar{y}_i = \frac{\sum y}{n}$) , n, y_i , $\hat{y}_i$ is the same as Equation (1).

7.2.3.2 Independent variables

According to the first hypnosis, as explained previously, there are two main independent variables which are the predictive ability of ML algorithms and the predictive ability of accounting information.

1- *First Independent variables : the predictive ability of ML algorithms to predict stock price:*

The predictive ability of ML to predict stock price was measured using 6 algorithms. These algorithms involve Logistic Regression (LR), Neural Networks (NN), Random Forest (RF), Decision tree (DT), K-Neighbour (KN), and support Vector Machine (SVM). which are distinguished and most effective in predicting stock prices (Islam & Nguyen, 2020). because of their data-driven self-learning nature and generalization, once the algorithm learns the data, it can predict the unseen or future part of the data even if the given data is not smooth (Islam & Nguyen, 2020). The researcher used an anaconda Python program to build a prediction model and utilized LMST (Long Short-Term Memory) and ARIMA. These algorithms are extremely powerful for time series. It can capture historical trend patterns and predict future values with high accuracy. (Nabipour et al., 2020; Wang et al., 2021; Chiniforoush & Shabgahi, 2021).

2- *Second Independent variables: The predictive ability of accounting information to predict stock prices:*

The researcher utilized a multiple linear regression model to measure the predictive ability of accounting information to predict stock prices using financial ratios. The purpose of the regression model is examination the predictive ability of ratios derived from financial statements represented in profitability ratios, liquidity ratios, leverage ratios, valuation ratios, operational efficiency ratios, governance, credit rating, and Industry to predict stock price (Gao et al., 2021), which can be expressed as follows:

$$\mathbf{P_t} = \boldsymbol{\alpha_0} + \sum_{i=1}^{n} \boldsymbol{\beta_i}\, \boldsymbol{LN\ X_i} + \boldsymbol{\varepsilon_t} \qquad \mathbf{(5)}$$

Where: P_t represents closing stock prices in the day t, and X_i is the explanatory variables that affect stock prices, these variables were chosen based on surveying the opinions of financial analysts in Egypt regarding the significant financial ratios for measuring fundamental financial analysis that influence closing stock prices, described in Index (1). α_0 is constant (the value for y-intercept), β_i is the regression coefficients representing the change in the stock price for a one-unit change in the respective information accounting for independent variables and ε_t is the model's error term.

7.2.4 The case study procedures for measuring the ability of ML algorithms to predict stock Price:

The researcher did a series of procedures to measure the ability of ML algorithms to predict stock Price as the first independent variable of the study. These procedures include the Dataset analysis stage, Data Pre-Processing stage, and Data Processing stage. These procedures be described as follows:

Dataset analysis: For Testing the predictive ability of ML algorithms to predict stock price. The researcher employed a case study approach using the closing prices of Telecom Egypt company's stocks ranging from 2019 to 2022, which is quarterly financial statements for 4 years for Telecom Egypt stocks, a total of 1155 historical daily observations. Analysis data Was loaded from the Yahoo Finance Database, which offers free historical and real-time stock market data. The base features in this data were daily stock open prices, highest prices, lowest prices, Closed prices, volume, and adjusted close. Splitting the available dataset into training and testing datasets is recommended when performing data analytics using machine learning. (Kelleher and Tierney, 2018). The researcher uses the oldest 80% of the data as the training set and saves the most recent 20% *as* the testing set.

Data Pre-Processing stage: This stage involves data discretization (data reduction, especially for numerical data), data transformation (Normalization), data Cleaning, removing entries with incomplete or invalid information and filling in missing values, data Integration, and developing a Python code to calculate a series of technical indicators.

Data Processing stage: After the dataset is transformed into a clean dataset, the dataset is divided into training and testing sets to evaluate. The researcher used 80% of the data for modeling, where 75% of this dataset was used as a training dataset (80% X 75%= 60%) and 25% of the dataset was used as a validation dataset (80% X 25% =20%). And the rest of the total data, 20%, is *used* for testing the model as a testing dataset (Jan 2021). Here, the training values are taken as the more recent values, at 80 percent of the total dataset. Testing data is kept *as* 20 percent of the total dataset **using Python coding as following steps**:

Step (1) Importing Libraries: Python libraries make it very easy to adjust the data and perform typical and complex tasks with a single line of code. The Python libraries used by the researcher like Pandas, Matplotlib, Seaborn , and Sklearn , by running the following codes:

```
In [1]: import datetime
        import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import math
        from sklearn.preprocessing import MinMaxScaler
        import matplotlib.pyplot as plt
        plt.style.use('fivethirtyeight')
        from sklearn import svm
        from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier, VotingClassifier
        from sklearn.neighbors import KNeighborsClassifier
        from sklearn.model_selection import train_test_split, GridSearchCV
        from sklearn.metrics import confusion_matrix, classification_report, mean_squared_error, accuracy_score
```

Step (2) Evaluation Metrics: The researcher employed the Validation set to compare the prediction accuracy between several supervised machine learning theories that have binary classification outputs such as Logistic Regression (LR), Neural Networks (NN), Random Forest (RF), Decision tree (DT), K-Nighbour (KN), and Support Vector Machine (SVM), to find the best one of them. These regression models are used for predictions and comparison. The researcher tested the model's performance using the Matthews Correlation Coefficient (MCC) and Accuracy (ACC) for Performance' accuracy assessment, as follows:

1- **MCC**: is a confusion matrix (2*2) with True Positive (TP), False Positive(FP), True Negative(TN), and False Negative(FN), respectively.

$$\mathbf{MCC} = \frac{\boldsymbol{TP \cdot TN - FP \cdot FN}}{\sqrt{\boldsymbol{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}}}$$

2- **Accuracy:** The accuracy of prediction is defined as follows:

$$\textbf{Accuracy} = \frac{\textbf{the number of days that model correctly classified the testing data}}{\boldsymbol{total\ number\ of\ testing\ days}}$$

According to table (2), the NN model has the highest accuracy, at only 58.2%. Then, K-Neighbour was 56.4%, and the Decision tree was 54.4%. Random forest had the lowest accuracy, at 40.6%. MCC showed consistent results. Such a result can be explained by the semi-strong efficient market hypothesis, which states that all public information is calculated into a stock$'s$ current stock price, meaning that neither fundamental nor technical analysis can be used to achieve superior gsains.

Table 2: accuracy of machine learning algorithms prediction

Model	LR	NN	RF	DT	KN	SVM
Accuracy	46.5%	58.2%	40.6%	54.4%	56.4%	53.2%
MCC	0.0725	0.457	0.0693	0.1639	0.285	0.1546

Source: Jupyter Notebook output

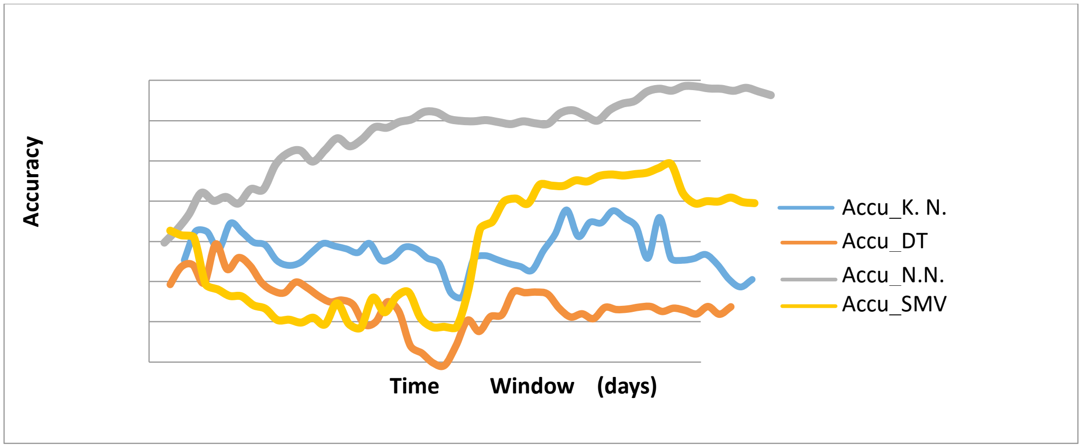

chart 1: Long--Term Prediction Accuracy

Source: Jupyter Notebook output

Furthermore, Chart (1) clearly shows that the accuracy of SVM and NN models increases with the time window. The NN model gives the highest accuracy when the time window is 55 days (80%). It's also the most stable model. For the evaluation metric, NN activation (functions) such as LMST and ARIMA coding are used to predict **stock prices.**

Step (3) Exploratory Data Analysis (EDA): During this step the researcher using visual tools, such as statistical and graphical tools, to analyzing the data and identify trends and patterns. While performing the EDA of the telecom Egypt Stock Price data, the researcher analyzed how stock prices have moved over the period and how the end of the quarters affects the prices of the stock Chart (2).

Chart 2: EDA of The Telecom Egypt Stock Prices
Source: Jupyter Notebook output

Chart (3) clear that the prices of telecom Egypt stocks showing an upward trend, as depicted by the plot of the closing price of the stocks. Moreover, the telecom Egypt Stock Price distribution plot, Chart (4) showed that two peaks, which means the daily data has varied significantly in the two regions. The Volume data is left-skewed, which means that only volume data contains outliers.

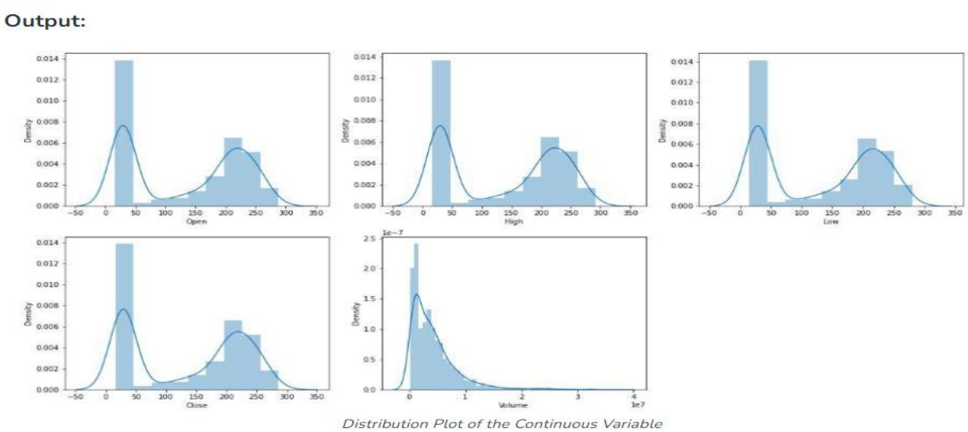

Chart 3: Distribution of The Telecom Egypt Stock Prices
Source: Jupyter Notebook output

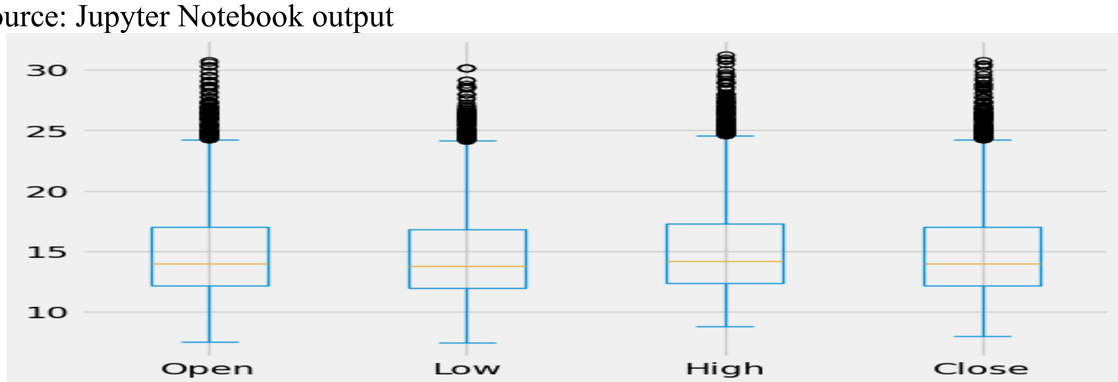

Chart 4: Boxplots analysis of the telecom Egypt Stock Prices
Source: Jupyter Notebook output

Step (4) Descriptive Statistics: As shown in Table (3), 1155 rows of data are available, and each row has 7 different features or columns. Table (3) describes the key features of the data and summarizes their statistical differences. This table reveals that the mean of the close prices was 15.687 with a standard deviation of 5.087, the min value was 7.99, and the max value was 30.75. While the mean of the open prices was 15.707, with a a standard deviation of 5.0947, the min value was 7.5, and the max value was 30.74. This indicates that the mean of the daily observations was decreased for close prices compared to open prices. It is also clear from the results that there is a significant discrepancy between the means values. In addition to the higher standard deviation for open prices than close prices, a low a standard deviation for close prices indicates that the data points tend to be close to the mean. In contrast, a high a standard deviation for open prices indicates that the data are spread out over a large range of values. In other words, open prices are more homogeneous, and closed prices are less homogeneous. Therefore, stock price predictions using the close prices will be more accurate than those using open prices.

Table 3: Descriptive Statistics

```
[1155 rows x 7 columns]

[50]: df.describe()
[50]:
```

	Close	Open	High	Low
count	1155.000000	1155.000000	1155.000000	1155.000000
mean	15.687039	15.707351	15.942918	15.457818
std	5.087215	5.094730	5.206612	4.984361
min	7.990000	7.500000	8.780000	7.400000
25%	12.160000	12.165000	12.345000	11.950000
50%	13.990000	14.000000	14.160000	13.800000
75%	17.000000	17.000000	17.245000	16.830000
max	30.750000	30.740000	31.230000	30.170000

Step (5) Creating a Training Set and Test Set: A new dataset was generated based on close prices obtained in step (3) and this data is split into 80% of the dataset as a training set, where 75% of this dataset used as a training dataset (80% * 75%= 60%) While 25% of the dataset is used as validation dataset (80% *25% = 20%). And 20 % of the dataset as a testing set (Jan, 2021). The training set is used to train the ML model. The Validation set is employed to compare the performance of several models to find the best one. A test set was used to evaluate the final model's accuracy using the Time-Series-Split class from the Scikitlearn library (Gierbl, 2021). The benefit of using the Time Series split is that it evaluates data samples at regular time intervals by executing the following code:

```
In [53]: #Create a new dataframe with only the 'Close column
         data = df.filter(['Close'])
         #Convert the dataframe to a numpy array
         dataset = data.values
         #Get the number of rows to train the model on
         training_data_len = math.ceil( len(dataset) * .8)
         training_data_len

Out[53]: 924
```

The research sample consists of Egyptian non-financial listed firms, and according to the output of the Time Series split code the training set equals 924 daily observations. where 75% of this dataset used as a training dataset (924 * 75%= 693 daily observations) While 25% of the dataset is used as validation dataset (924 *25% = 231 daily observations).

Step (6) Check the outliers values to ensure that there are none in training set by Printing the Data Frame Shape, by running the following code:

```
#Print the shape of Dataframe  and Check for Null Values
print(“Dataframe Shape: “, df. shape)
print(“Null Value Present: “, df.IsNull().values.any())

]:    Dataframe Shape: (924, 6)
      Null Value Present: False
```

It’s clear from the Data Frame Shape code output that there are no null values (outliers) in the data frame of the training dataset (924 daily observations).

Step (7) Normalizing the Dataset: To decrease the memory consumption of the data set in the table, and then achieve more accuracy, the researcher scaled the stock price values between 0 and 1, to ensure that the data is not spread out in huge values. To perform this, the researcher is used the MinMaxScaler class of the scikitlearn library by running the following code:

```
In [60]: #Scale the data
         scaler = MinMaxScaler(feature_range=(0,1))
         scaled_data = scaler.fit_transform(dataset)
         scaled_data

Out[60]: array([[0.90509666],
                [0.86818981],
                [0.90114236],
                ...,
                [0.20386643],
                [0.20342707],
                [0.20035149]])
```

The scaler code output showed that all the stock price values are in the range 0 to close 1.

Step (8) Data Processing For LSTM: Before introducing the data into the Long Short-Term Memory (LSTM) model, training and testing datasets should be transformed in a way that the LSTM model can be interpreted. By transforming them into 3D NumPy arrays (Number of Samples, 1, Number of Features). by running the following code:

```
In [63]: #Convert the x_train and y_train to numpy arrays
         X_train, y_train = np.array(X_train), np.array(y_train)
         #Reshape the data
         X_train = np.reshape(X_train, (X_train.shape[0], X_train.shape[1], 1))
         X_train.shape

Out[63]: (864, 60, 1)
```

The output of the NumPy arrays code showed that the number of predictions in the sequence, which represented the length of the input sequence or the number of timesteps in the model (time series of daily prices), is 864 daily observations. The number of features in each prediction, which represented the technical indicators (such as the moving average or the RSI) of the input data or the number of hidden units in the LSTM model, is 60 features. Finally, the number of output values in each prediction represents the dimensionality of the output data or the number of target variables in the model (the predicted closing price for the next day) is 1.

Step (9) Building the LSTM Model for Stock Price Prediction: The Sequential Keras model is employed to build the LSTM Model which has 50 units as one layer, followed by one dense Layer of one neuron. Also, the model is compiled using Adam Optimizer, and the Mean Squared Error as the loss function, by running the following codes:

```
In [69]: #Build the LSTM model
         model = Sequential()
         model.add(LSTM(50, return_sequences=True, input_shape= (X_train.shape[1], 1)))
         model.add(LSTM(50, return_sequences= False))
         model.add(Dense (25))
         model.add(Dense(1))

In [70]: #Compile the model
         model.compile(optimizer='adam', loss='mean_squared_error')

In [71]: #Train the model
         model.fit(X_train, y_train, batch_size=1, epochs=1)

         864/864 [==============================] - 25s 22ms/step - loss: 0.0031

Out[71]: <keras.src.callbacks.History at 0x2349577fed0>
```

From the above output can observe that the loss value has decreased exponentially over time from 1 to 0.003. After building the model, the testing dataset is created for 60 epochs with a batch size of 8 by running the following codes:

In [72]:
```
#Create the testing data set
#Create a new array containing scaled values from index 925 to 1155
test_data = scaled_data[training_data_len -60: , :]
#Create the data sets x_test and y_test
x_test = []
y_test = dataset[training_data_len:, :]
for i in range(60, len(test_data)):
  x_test.append(test_data[i-60:i, 0])
```

In [73]:
```
#Convert the data to a numpy array
x_test = np.array(x_test)
```

In [74]:
```
#Reshape the data
x_test = np.reshape(x_test, (x_test.shape[0], x_test.shape[1], 1))
```

In [75]:
```
#Get the models predicted price values
predictions = model.predict(x_test)
predictions = scaler.inverse_transform(predictions)
```

```
8/8 [==============================] - 1s 14ms/step
```

Step (10) Prediction of the Telecom Egypt stock prices: In this step, a deep learning artificial recurrent neural network (RNN) is employed to design the ML model to Predict Telecom Egypt's close prices based on the model trained using the LSTM network on the testing dataset, by running the following code.

In [75]:
```
#Get the models predicted price values
predictions = model.predict(x_test)
predictions = scaler.inverse_transform(predictions)
```

```
8/8 [==============================] - 1s 14ms/step
```


Step (11) :Comparing Predicted vs. Actual Close Prices Using Graphs by Running the Following Code:

In [77]:
```
#Plot the data
train = data[:training_data_len]
valid = data[training_data_len:]
valid ['Predictions'] = predictions
#Visualize the data
plt.figure(figsize=(16,8))
plt.title('Model')
plt.xlabel('Date', fontsize=18)
plt.ylabel('Close Price USD ($) ', fontsize=18)
plt.plot(train['Close' ])
plt.plot(valid[['Close', 'Predictions']])
plt.legend(['Train', 'Val', 'Predictions'], loc='lower right')
plt.show()
```

Chart (5) from step (11) illustrates the comparison between the predicted and actual stock closing prices using the SMA. In the chart, blue represents the training set, orange represents the actual prices in the testing dataset, and yellow represents the predicted prices for the testing set. When the yellow line is above the orange, it indicates an upward trend, and when the orange is above the yellow, it indicates a downward trend. The chart shows that the LSTM model closely predicts the actual stock price trends, although it tends to the model give smaller prediction values than the actual values. The model′s accuracy could be improved by training with more data and adding more LSTM layers.

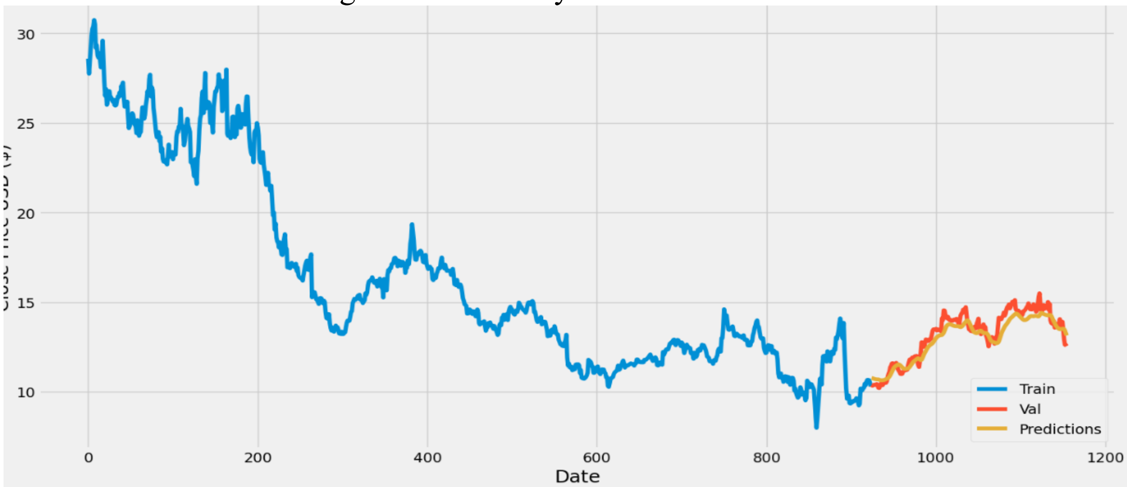

Chart 5: The trend chart of the Telecom Egypt stock prices

Source: Jupyter Notebook output

Step (12) Assessment Accuracy of the predictions: The researcher employed the MAE, RMSE, MAPE, and R^2 to assess the accuracy of the predictions prices, using the following codes :

```
# Calculate Accuracy metrics
actual_values = df['Close']
predicted_values = df['ema']

mae = mean_absolute_error(actual_values, predicted_values)
rmse = mean_squared_error(actual_values, predicted_values, squared=False)
mape = mean_absolute_percentage_error(actual_values, predicted_values)
r2 = r2_score(actual_values, predicted_values)

print(f"Mean Absolute Error (MAE): {mae}")
print(f"Root Mean Squared Error (RMSE): {rmse}")
print(f"Mean Absolute Percentage Error (MAPE): {mape}")
print(f"R-squared (R²): {r2}")
```

Table (4) shows the accuracy metrics of the LMST model. The model offers a relatively low MAE (0.40989), suggesting that the model makes reasonably accurate predictions. Is MAE the same? The RMSE is also relatively low (0.5623), suggesting that the model makes reasonably accurate predictions. However, the MAPE is very low, suggesting that the model makes very accurate predictions relative to the scale of the target variable. In this case, the R-squared value is very high, suggesting that the model is a very good fit for the data.

Table 4: Assessment Accuracy of the Predictions

MAE	RMSE	MAPE	R^2
0.409892764	0.56225472	0.026251222	0.96777406

Source: Source: Jupyter Notebook output

7.2.5 Testing the ability of accounting information to predict stock prices:

The researcher utilized the Event study approach to measure the predictive ability of accounting information to predict stock prices using a multiple linear regression model involves various financial ratios and other relative accounting information related to stock price predictions. As in the case study, the event study was conducted using financial data disclosed in the quarterly financial reports of the Telecom Egypt company during 2019-2022.

7.2.5.1 Event Study Approach:

Using publicly available financial news for Telecom Egypt Company from January 2019 to December 2022. This period witnessed a severe economic downturn in 2019- 2020 (COVID-19 period), followed by a modest recovery in lastly of 2021- 2022. The related accounting information and news on financial events are extracted from HTML using online resources, such as Google Search, Yahoo Finance, Mubasher Information Egypt, The Egyptian Exchange, and Telecom Egypt Website.

7.2.5.2 The event study procedures for measuring the ability of accounting information to predict stock Price:

The event study predicts close stock prices at and around the time the event occurred according to the following steps, which were determined by Awaad (2022), as shown in Figure (3).

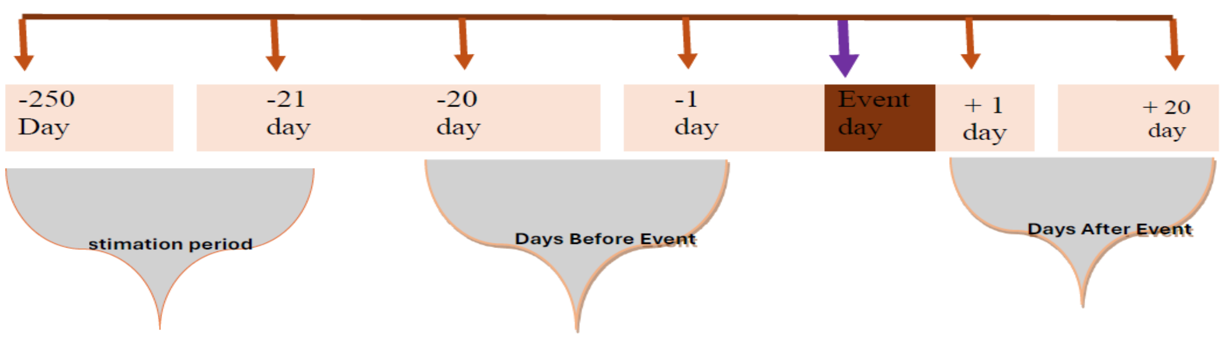

Figure (3) Event Study Methodology

Step(1) Identifying Event: Event is the identification of specific and important events, such as the date of publication of quarterly financial reporting, the date of announcement of dividend earnings, and the date of announcement of any changes in the composition of the board of directors, the shareholder structure, or a change in company leadership (Awaad, 2022). Regarding the current study, there are 20 events in total from the publication of quarterly financial reporting News and 547 from other News. The dataset is split temporally into the training and testing sets, with the data from 01/01/2019 to 18/6/2021 as the training dataset and the data from 22/06/2021 to 21/10/2023 as the testing dataset. **There are about 425 events in the training set and 142 events in the testing set.**

Step (2) Identifying Event Window Period: The event window period is a period before and after a specific event that is used to analyze the event's impact (Awaad, 2022). In this study, the event window was the twenty trading days before and after the announcement **(-20/+20 days).**

Step (3) Identifying Event Estimation Period: The event estimation period refers to the time before an event during which parameters for a stock price prediction model are calculated(Awaad, 2022). This model is then used to calculate stock prices, which measure the event's impact on the stock market. For this research, the event estimation period **is 250 trading days** before the announcement.

Step (4) Building a Linear Regression Model to **predict stock prices:** This research constructs a linear prediction model using a state-of-the-art classification model. Given a training set (d1, y1), (d2, y2), ..., (dN, yN), where n ∈ [1, N], dn is an event, and yi ∈ {+1,−1} is the output class (stock prices). The output of (class +1) represents that the stock price will increase the next day/week/month after the event, and the output of (Class -1) represents that the stock price will decrease the next day/week/month after the event. These features {(Class + 1), (Class – 1)} are determined by a multiple linear regression model, which includes the accounting variables affecting stock price, to estimate coefficients parameters of independent variables, according to the model proposed by Gao et al., (2021):

$$\mathbf{P_t = \alpha_0 + \sum_{i=1}^{n} \beta_i X_i + \varepsilon_t} \qquad (5)$$

Where P_t and X_i were explained previously [X_i identified in index (1)].

Step (5): Running the accounting data previously identified using Stata 15 software to estimate the correlation coefficients between stock price and accounting information. The coefficients (β1 .. βi) are estimated using the ordinary least squares method (OLS) . The coefficients minimize the sum of the squared differences between the predicted and actual stock prices.

Step (6): Evaluating the significance of the model using the F-test and using the T-test to Evaluate the significance of the explanatory variables X_i. Finally, determining the R^2 value at a confidence level of 95%

Step(7): Testing the impact of events on the prediction model by evaluating the polarity of stock changes across three time intervals: short-term (1 day), medium- term (10 days), and long-term (20 days). This involves comparing news representations based on events with those based on bag-of-words and contrasting the performance of the deep neural network model with that of the SVM model (Yang, 2016).

7.2.5.3 Evaluation Accuracy of the Predictive Ability of Accounting Information to Predict Stock Price:

The researcher employed mean and standard error as performance metrics to evaluate the accuracy of the accounting information-based model to predict stock price. T-test for statistical significance was conducted by comparing the mean and standard error of the actual stock prices with the predicted stock prices. The model is considered accurate if there is no significant difference between the actual and predicted prices. This implies that the model can effectively forecast future stock prices.

7.2.5.4 Empirical Rustle for Event Study:

According to table (4) Panel (A), the results showed that R^2 is high (98.6%, 95.4%, and 97.3%, respectively, across all three different periods). RMSE is low (0.064077, 0.068409, 0.066099, respectively, across all three different periods), and the significance of F > Prob is observed at 0.000 at the 5% significance level across all three different periods. Additionally, the results showed that most accounting variables significantly correlate with stock prices, less than the 5% significance level across all three different periods. It suggests that the linear regression model is a good methodology for predicting stock prices, where the R2 values for the prediction linear regression model are above 90% across all three different periods, it indicates that the accounting information explains greater than 90% of changes in stock price values.

Also, Table (4) Panel (A) shows that the regression model using daily news titles achieves the best prediction because it has the highest explanatory power, 98.6%, indicating that accounting information is a good indicator for the short-term volatility of stock prices. The empirical results confirm the conclusion of Tetloc et al., (2008) that there is a one-day delay between the price response and the information embedded in the news. Considering the previous analyses, the best model that can be used to predict daily stock prices in the Egyptian financial market can be formulated as follows:

$P_{1\ day}$ = 119.887+ 38.75 ROA +1.92 ROE + 2.076 PS + 18.77 DIV – 2.696 S-Growth – 2.093 OPM +0.0471 OCFM + 0.0278 CaR +1.186 BVS -C0.0243 PS – 1.569 Inv-Turn – 0.0026 TA-Turn + 0.0084 TANG + 7.687 Size + 2.163 Rating +35.654 CG – 28.171 MSH + 4.061 CP (6)

The researcher conducted a T-test to evaluate the reliability and accuracy of the model (6) in predicting stock prices. This was done by comparing the means and standard errors of the predicted stock prices generated by the model with the actual stock prices in the same period to determine if there is a significant difference between them. Table (4) Panel (B) presents the results of the T-test. The mean of the actual stock prices is 15.94292, while for the predicted stock prices, it is 15.45782, with a difference of 0.4851. The standard error for the actual stock prices is 0.1532019, while for the predicted stock prices, it is 0.1466623, with a difference of 0.0065396. However, the p-value for the T-test is 0.5382, which is greater than the significance level of 0.05. This suggests that the observed differences between the actual and predicted prices of Telecom Egypt Company are not statistically significant. Furthermore, the T-test results indicate that the correlation between the actual and predicted stock prices is 0.9896. **This suggests that the model (6) can predict stock prices with an accuracy of above 98%.**

Table 4: Statistical Results of the Event Study

Panel A: OLS Results						
Model (variables)	**P ($Period_1$: 1 day)**		**P ($Period_2$: 10 days)**		**P ($Period_3$: 20 days)**	
	β	**P-Value**	**β**	**P-Value**	**β**	**P-Value**
Constant	119.87	0.020	170.456	0.027	237.67	0.034
ROA	38.75	0.011	28.802	0.000	20.965	0.010

ROE	1.92	0.048	1.628	0.038	1.352	0.028
EPS	2.07	0.000	1.670	0.000	2.05	0.000
DIV	18.77	0.0141	16.642	0.031	15.368	0.009
S_growth	-0.0017	0.920	-0.0207	0.025	-0.0358	0.056
GPM	-2.696	0.0355	-1.673	0.004	-2.2739	0.000
OPM	-2.093	0.0212	-3.953	0.053	-4.883	0.051
OCFM	0.0471	0.0484	0.089	0.000	0.0374	0.000
CaR	0.0278	0.0444	0.0218	0.005	0.0115	0.000
QR	0.0328	0.0876	0.4307	0.992	0.846	0.073
CR	0.843	0.051	0.605	0.066	0.5468	0.085
DR	0.0138	0.0978	0.0157	0.031	0.0116	0.003
ICR	-0.0088	0.0711	-0.00185	0.262	-0.0553	0.086
DE	-0.0285	0.0935	-0.030	0.445	-0.0426	0.796
PE	-7.3589	0.0903	-9.634	0.096	-8.019	0.075
PCF	65.37	0.0691	59.64	0.043	67.89	0.046
BVS	1.186	0.000	1.683	0.003	1.214	0.007
PS	-0.0243	0.0203	-0.0049	0.037	-0.0075	0.045
Inv-Turn	-1.569	0.027	-1.954	0.029	-1.658	0.038
Rec-Turn	-0.004	0.096	-0.00856	0.078	-0.00612	0.086
Pay-Turn	-4.446	0.093	-5.197	0.073	-3.091	0.099
FA-Turn	0.078	0.717	0.00345	0.957	0.0158	0.808
TA-Turn	-0.0026	0.037	-0.0069	0.016	-0.0092	0.000
TANG	0.0084	0.0441	0.0082	0.036	0.0083	0.026
CAPEX	2.387	0.054	2.714	0.014	2.687	0.000
Age	0.00186	0.103	0.0096	0.263	0.0058	0.138
Size	7.687	0.0349	6.934	0.028	7.342	0.016
Rating	2.163	0.010	3.185	0.023	1.432	0.001
CG	35.654	0.007	21.496	0.000	26.75	0.004
MSH	-28.171	0,028	-27.402	0.021	-27.809	0.000
CP	4.061	0.043	4.936	0.005	4.888	0.161
F-statistic	46.56		36.18		42.68	
Prob > F	0.000		0.000		0.000	
R-squared	0.986		0.954		0.973	
Adj. R-squared	0.923		0.903		0.947	
RMSE	0.064077		0.068409		0.066099	
Panel B : T- Test Results						
	Actual	**Predicate**	**Actual**	**Predicate**	**Actual**	**Predicate**

	Prices	Prices	Prices	Prices	Prices	Prices
Mean	15.94292	15.45782	15.81452	15.68704	15.70735	15.68704
Std. Err.	0.1532019	0.1466623	0.1514219	0.1496887	0.1499099	0.1496887
Prob(T > t)	0.5382		0.2324		0.4746	
correlation coefficient	0.9896		0.8838		0.9236	

7.2.6 Comparison analysis

This section discusses the comparison between output from the two models, model' ML and accounting information' model above. Where Figure (4) displays the comparison results graphically

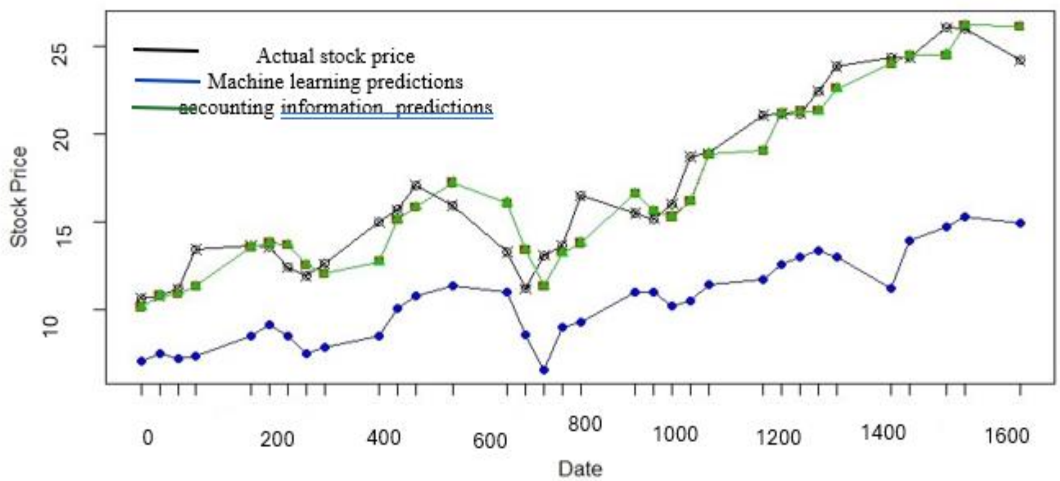

Figure (4) Comparison analysis of two prediction models by the actual stock price

Figure (4) shows that the accounting information prediction model outputs are very close to the actual stock price compared to machine learning predictions.

7.2.7Analysis and Discussion Results of the First Research Hypothesis

The first hypothesis was formulated to test the impact of ML algorithms on the traditional role of accounting information in stock price Predictions for Egyptian listed firms by testing this Null Hypothesis:" **Machine learning algorithms do not replace accounting information in predicting stock prices for Egyptian listed firms".** This test was done using a case study approach, and an event study approach, to predict the close stock prices of Telecom Egypt.

The results of the comparative analysis revealed that a linear regression model based on accounting information outperformed the ML algorithms model in predicting stock prices for Egyptian Telecoms company. Where the accounting information model achieved an R2 value of 98% compared to 96% for the ML model. Additionally, the accounting information model exhibited a significantly lower RMSE of 0.06 compared to 0.562 for the ML Algorithms model.

Therefore, the observed dataset does not provide strong evidences to reject the null hypothesis in favor of the alternative hypothesis. Consequently, the researcher concluded that the Alternative Hypothesis which states that" **Machine learning algorithms replace accounting information in predicting stock prices for Egyptian listed firms**." **Is Rejected**.

These findings indicate that accounting information still surpasses ML algorithms in predicting stock prices. Despite the advancements in ML, traditional accounting data continues to offer valuable insights into a stock′s future movements, demonstrating that ML algorithms cannot fully replace it in financial predictions. However, artificial intelligence (AI) tools, including ML algorithms, can complement and enhance the traditional role of accounting information. By integrating these tools, accountants can strengthen their professional capabilities and competitive advantage. Therefore, accountants must embrace AI and ML technologies to stay ahead in the evolving financial field.

7.3 Testing and Discussion of the Second and Third Research Hypothesis:

The researcher utilized an empirical Study approach to test the second and third hypotheses. An empirical study aimed to test whether machine learning algorithms have more predictive ability than accounting information in predicting cash holdings. Additionally, it aimed to investigate if integration between ML algorithms and accounting information improves the predictive ability of accounting information in predicting cash holding, compared to exhibited by each separately.

7.3.1 Empirical Study Sample and Data Collection:

The research population involves all non-financial firms listed on the Egyptian Stock Exchange (EGX) during the period from 2029 to 2022. A selective sample of firms was chosen based on specific criteria for sample selection, banks and financial firms are excluded because they are subject to different regulatory requirements and corporate governance practices. In addition, financial firms have their unique characteristics and different operations. Also, firms whose financial statements are prepared in a foreign currency are excluded, and firms whose financial reporting date is different from 12/31 are excluded. After excluding observations of firms with missing data, the final sample was 564 firm-year observations. To prevent the overfitting problem causing poor predictions with the unseen data, the researcher split 80% of the dataset as training set and took the remaining 20% *as* testing set, as discussed previously in the Data processing section 7.2.4.

7.3.2 The Second Hypothesis Variables:

In the light of the second research hypothesis which states that "**Machine Learning Algorithms outperform traditional models based on accounting information in predicting cash holding"**, the research involves two independent variables, and one dependent variable can be measured as follows. **The first independent variable** is the predictive ability of ML algorithms in predicting cash holding. The researcher used various algorithms, such as Multiple linear regression, Decision tree regression, Random Forst, support vector regressor, and Neural networks, to measure the predictive ability of ML machine learning algorithms, (Ozgur et al., 2021). The researcher evaluated these algorithms based on accuracy and MCC metrics, as discussed previously in the Evaluated Metrics section 4. The results of table (5) are reported that SVR is more accruate metric compared with MLR, DR, RF, and KNN algorithms in predicting cash holding

Table 5: Accuracy of machine learning algorithms prediction

Model	NN	SVR	DT	RF	MLR
Accuracy	51.17%	68.57%	57.73%	55.14%	49.36%
MCC	0.122	0.795	0.361	0.158	0.0161

Source: Jupyter Notebook output

Based on these results in Table (6), the researcher employed a **Support Vector regressor** to run the following linear regression with formula (6) to predict cash holding using the Anaconda program and Python software, (Ozlem and Tan , 2022).

$$\boldsymbol{Y} = \beta_0 + \beta_1\boldsymbol{X}_1 + \beta_2\boldsymbol{X}_2 + \cdots + \beta_{\boldsymbol{k}}\boldsymbol{X}_{\boldsymbol{k}} + \varepsilon \qquad (6)$$

where Y: response cash holding prediction, Xk: kth accounting variables selected based on Ozlem & Tan (2022) [as described in index (2)], β_0 : constant, β_k : coefficient of explanatory variables, and ε : Error term.

The second independent variable is the predictive ability of accounting information in predicting cash holding. This variable is measured by various financial ratios based on financial statement elements related to measuring cash holding, which is classified in index (2) based on (Ozlem & tan, 2022)

7.3.3 The procedures of Empirical Study for the second research hypothesis:

The researcher used two types of cash-holding prediction models from the literature to evaluate the predictive ability performance as benchmarks. The first model is financial ratio-based logistic regression (accounting information model), proposed by Ozlem and Tan (2022). These ratios are identified by human experts . The second model is a cash holding prediction model developed by the researcher based on support vector regression (SVR) using raw financial. Finally, to compare the prediction performance of different cash holding prediction models, the researcher adopts two distinctive performance evaluation metrics, RMSE and MAPE, as performance evaluation metrics.

7.3.4 Empirical Results for the second research hypothesis:

To testing the second research hypothesis, the researcher followed the same steps previously explained in the first hypothesis to predict cash holding using accounting information once and ML algorithms once again**.** The results in Table (6) are showed that the model (2) has the lowest MAPE and RMSE (0.626 and 0.137) compared with the model (1) (0.719 and 0.212) in cash holding predictions. These results suggested that ML algorithms model has more accurate predictability than accounting information model in predicting cash holding.

Table 6: Performance Metrics for prediction models

Prediction Model	MAPE	RMSE
Model (1) with Financial ratios (accountting information)	0.719	0.212
Model (2) with raw financial data (machine learning)	0.626	0.137

Source: Jupyter Notebook output

From the above discussion, the researcher can be concluded that there is a significant difference in predictive ability between model(1) and model(2). Using machine learning significantly impacted the model's performance regarding cash holding predictions compared to traditional financial ratios only. Thus, the second research hypothesis (H2) states that " **Machine Learning Algorithms outperform traditional models based on accounting information in predicting cash holding**." **It is accepted**. This result is consistent with prior research findings (Jin et al., 2023; Ozgur et al., 2021), which provided evidence that the predictive ability of ML algorithms outperformed the predictive ability of accounting information in cash-holding predictions.

7.3.5 Analysis and Discussion Results of the Second Research Hypothesis:

The findings of this hypothesis suggested that the Support Vector regressor (SVR) model exhibits better prediction performance in predicting cash holding compared with regression models based on accounting information. These results suggested that machine learning algorithms can be highly useful in improving accounting information's predictive ability, thereby enhancing financial information's relevance to stockholders and adding value to decision-makers. The researcher attributes this outperformance for machine learning algorithms to several reasons; the machine learning algorithms used the archival training data more consistently and systematically compared with soft data used by accountants, which reduced estimation errors. Also, accountants' estimates may include forward-looking information, such as expected inflation, the state of the economy, and expected changes in exchange rates, that machines obviously ignore. Thereby positively affecting the reliability and relevance of financial reports. Accordingly, the superiority of machines over accountants in accounting estimations is not real superiority.

7.4 Testing and Discussion of the Third Research Hypothesis:

Using the same empirical approach used in testing the second hypothesis, the researcher tested the third hypothesis, which states that "**Integrating accounting information with machine learning Algorithms as Business partners, improves predictive ability compared to that exhibited by each separately in predicting cash holding for Egyptian listed firms**." As is the case in the second hypothesis, the researcher investigated the predictive ability of the ML algorithms model, then tested the predictive ability of the accounting information model, after that testing this hypothesis by running the traditional cash holding prediction model using ML algorithms and comparing RMSE and MAPE to all three models separately.

7.4.1 Empirical Results for the second research hypothesis:

Limiting to the same 23 raw financial data items in index (2), The results in table (7) are showed that model (3) has the lowest RMSE of 0.019 and the lowest MAPE of 0.325 among the applied support vector regressors compared with the two other models. The model has more accurate predictions for holding cash than the other models. This result suggests that when the number of financial statement elements used in the model is increased, the predictive ability of the model is improved significantly. Thus, using ML algorithms beside accounting information supports cash holding predictions compared to traditional financial ratios or ML algorithms both separately. This result consistence with prior research findings (Jin et al., 2023; Ozgur et al., 2021), which provided evidence that the applications of ML algorithms in accounting systems support the predictive ability of accounting information. Thus, the third research hypothesis (H3), which states that "**Integrating accounting information with machine learning Algorithms as Business partners, improves predictive ability compared to that exhibited by each separately in predicting cash holding for Egyptian listed firms**." **is Accepted**.

Table 7: Support Vector Regression Results

Model no	Model predictors	MAPE	RMSE
Model (1)	Financial ratios (accounting information)	0.631	0.127
Model (2)	with raw financial data (machine learning)	0.670	0.116
Model (3)	financial ratios+raw financial data item	0.325	0.119

Source: Jupyter Notebook output

7.4.2 Analysis and Discussion Results of the third research hypothesis:

The results of the third research hypothesis suggested that the support vector regressor model outperformed in predicting cash holding. The accuracy of this model's predictions is improved when the SVR-based ML algorithms model is running along with the financial ratio based on accounting information. So, the researcher accepted the third hypothesis. These results imply that the interaction between ML algorithms and accounting information can improve the accuracy of the predictions of financial analysis, especially cash-holding predictions. **To summarize,** *ML algorithms and accounting information are business partners, They complement each other, and one cannot replace the other, as the accounting information disclosed in the financial statements, which is the final product of the accounting systems is the basic input upon which the predictions and financial analysis processes are based using machine learning.*

8. Conclusions, Recommendations, and Future Research:

The objective of this study is to investigate the impact of ML algorithms in improving the predictive ability of accounting information in financial predictions, particularly stock price and cash holding predictions for Egyptian nonfinancial listed firms from 2019 to 2022. In addition, the research aims to investigate whether the combination of accounting information and ML algorithms improved the accuracy of financial predictions. To fulfill the study objectives, the researcher analyzed the related prior literature that focused on the predictive ability of accounting information, and the predictive ability of ML algorithms to develop the research hypotheses.

Based on the relevant literature, the researcher hypothesized that ML algorithms replace accounting information in predicting stock prices. In addition, the researcher expected that ML algorithms have more accurate predictability than accounting information in predicting cash holding. Finally, the researcher supposed that the integration between ML algorithms and accounting information has a significant effect on financial prediction accuracy. After developing the relevant models and using a sample of 564 firm-year observations, the researcher found empirical evidence that while ML algorithms and accounting information mutually support each other, the predictive ability is significantly improved when financial ratios identified by accountants experts are combined with raw data.

This result indicates that the application of ML algorithms in the business environment doesn't affect the role of accounting information in financial predictions, which involves stock price predictions on the one hand. On the other hand, this study found that ML algorithms play an important role in improving the predictive ability of accounting information and ML algorithms and support each other. More importantly, the researcher finds evidence indicating that combining the financial ratios and the raw data items outperforms the ML algorithms model based on raw data only or the simple logistic regression model based on the financial ratios only. These results means that the model based on the financial ratios identified by accountants experts has not fully utilized accounting information contained within the financial statements. furthermore, it is possible to extract more useful predictive information from the raw data by constructing more advanced ML algorithms designed to use such data. Because the 23 raw data items represent only a small fraction of the a lot of possible raw financial data items that emerge from the accounting system. So, to improve the accuracy of prediction models need to be developed by performing a more systematically driven selection of model input from the readily available raw financial data items based on supplemental theory.

Additionally, ML algorithms excel in computational power and speed but lack human intuition and reasoning ability. Also, accountants need to adjust their perspective, understand the relationship between traditional accounting systems and ML, and adopt the applications of ML algorithms in their field. Designing accounting information systems based on ML algorithms requires collaboration between computer experts and professional accountants. While ML algorithms can handle routine tasks, accountants remain essential for tasks that require judgment and experience. But, intelligent financial software has security vulnerabilities that accountants must address. Accounting professionals should continuously enhance their skills and adapt to the evolving landscape. Although ML algorithms offer both opportunities and challenges to the accounting industry, they cannot fully replace human accountants, signaling the future direction of intelligent accounting. Relying solely on programmed and formalized accounting software is insufficient; tasks that require professional judgment still need the expertise and flexibility of experienced accountants. Additionally, accountants should be vigilant about security risks, actively working to prevent information leaks and other issues, and take on roles as both designers and supervisors of accounting systems in the era of intelligent accounting.

Based on the research results, the researcher suggests the following recommendations: First, forming a professional organization for the accounting profession in Egypt. The role of this organization is to support accountants by arranging training workshops and providing insights on how accounting professionals can embrace artificial intelligence and ML algorithms to stay ahead of the competition in the accounting field and take advantage of many opportunities in this rapidly changing and upgrading to encourage their technical capabilities and professional skills, especially in the machine learning era. Second, adopting machine learning algorithms in accounting systems by integrating these algorithms into day-to-day accounting tasks. An accountant can use their expertise and professional judgment to add value to the machine learning algorithms, which in turn helps them fulfill their objectives and improve their roles in the digitalized environment. Finally, more attention should be placed on empirical research on accounting intelligence that focuses on the accounting profession and its challenges because of artificial intelligence.

Based on the research results, the researcher suggests the following for future research: First, as this research is conducted on accounting information based on financial ratios only, the researcher recommends that future researchers replicate it on other data, such as narrative accounting information. Future researchers may investigate whether the usefulness of narrative accounting information is more efficiently extracted using advanced data mining. Second, as this research is conducted on the predictive ability of accounting information, the researchers recommend that future researchers replicate this study to investigate the effect of machine learning on other qualitative characteristics of useful financial information, such as comparability, verifiability, and timelines. Also, testing the effect of ML algorithms on detecting fraud in financial statements and accounting estimation forecasting. In addition, the researcher recommends that future researchers replicate this study in the financial sector and banks. Finally, the researcher recommends that in the future researchers retest the impact of artificial intelligence on the role of accounting information in a modern business environment using other artificial intelligence tools such as data mining or deep learning.

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Indexes

<table>
<tr><td colspan="3">Index (1)
factors for measuring the predictive ability of accounting information (Gao et al., 2021)</td></tr>
<tr><td colspan="2">Variables</td><td>Measurement</td></tr>
<tr><td rowspan="5">Financial Rati</td><td>Profitability ratios</td><td>- Return on Assets (ROA): The ratio of net income to the total assets
-Return on Equity (ROE): The ratio of net income to the total equity
-Earnings per share (EPS): the ratio of (Net Income - Preferred Dividends) to Number of Shares
-Annual dividends (DIV): The ratio of total dividend payments to the total assets
-sales growth (S_Growth) : Annual changes in sales growth (%)
-Gross Profit Margin (GPM): the ratio of (Revenue – Cost of Goods Sold) to Revenue
-Operating Profit Margin (OPM) : the ratio of Operating Profit to Revenue</td></tr>
<tr><td>liquidity ratios</td><td>-Operating Cash Flow Margin (OCFM): The ratio of Cash from operating activities to Sales Revenue
-Cash Ratio(CaR): the ratio of Cash and Cash Equivalents to Total assets
-Quick Ratio(QR): the ratio of (Current Assets – Inventory) to Current Liabilities
-Current Ratio (CuR): the ratio of Current Assets to Current Liabilities</td></tr>
<tr><td>Leverage Ratios</td><td>-Debt Ratio (DR): the ratio of the Total Debt to Total Assets
-Interest Coverage Ratio (ICR): the ratio of Earnings Before Interest and Tax to Interest Expense
-Debt to Equity Ratio(D/E): the ratio of Total Liabilities to Total Equity</td></tr>
<tr><td>Valuation Ratios</td><td>-Price to Earnings Ratio (P/E) : the ratio of Price per share to Earnings per share
-Price/Cash Flow (P/CF): the ratio of Price per Share to Operating Cash Flow per Share
-Book value per share (BVS): the ratio of net equity to number of issued Shares.
-Price to Sales Ratio (P/S): the ratio of Market Capitalization to Total Revenue.</td></tr>
<tr><td>Operational efficiency Ratios</td><td>-Inventory turnover (Inv-Turn): the ratio of cost of goods sold to the average of inventory.
-Receivables turnover (Rec-Turn): the ratio of Net Sales to Average accounts receivable.
-Payables turnover(pay-Turn): the ratio of Total supply purchase to Average Accounts Payable.
-Fixed asset turnover (FA-Turn): the ratio of Net Sales to Average of Fixed Assets
-Total asset turnover (TA-Turn): the ratio of Net Sales to Average Total Assets
Tangibility: The ratio of net fixed assets to the total assets
capital expenditure: The ratio of capital expenditure to the total assets
Age: Natural logarithm of the number of years that have passed since the entity was founded
SIZE: Natural logarithm of total assets</td></tr>
<tr><td colspan="3">Credit Rating (rating): The company's credit rating is measured by the Credit Rating index developed by Ateya (2021), which converts the issuer's credit rating at the end of the fiscal year into numerical values from 6 (higher rating) to 1 (Lower rating).</td></tr>
<tr><td colspan="3">Corporate governance (CG): by the index based on the characteristics of the board of directors, ownership structure, the characteristics of the audit committee, transparency, Risk management, and shareholders' right</td></tr>
<tr><td rowspan="2">Industry</td><td colspan="2">Market Share (MSH): Company Sales to Industry Total Sales ratio.</td></tr>
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</table>

Indexd (2)
financial elements for predicting cash holding predictions (Ozlem and Tan , 2022).:

Ratios	Definitions (Rowa data)
CASH	The ratio of cash and cash equivalents to the total assets
DIV	The ratio of total dividend payments to the total assets
SG	Annual change in sales growth (%)
SIZE	Natural logarithm of total assets
CAPEX	The ratio of capital expenditure to the total assets
CF	The ratio of the sum of pre-tax income plus depreciation to the total assets
IE	The ratio of interest expense to the total assets
NWC	The ratio of non-cash working capital to the total assets
TANG	The ratio of net fixed assets to total assets
STD	The ratio of short-term debt to the total assets
ROA	The ratio of net income to total assets
ROE	The ratio of net income to the total equity
AR	The ratio of accounts receivable to the total assets
AP	The ratio of accounts payable to the total assets
CR	The ratio of current assets to current liabilities
EPS	Earnings per share
ROIC	The ratio of net operating profit after tax to the total assets
NET MARGIN	The ratio of net income to net sales
PRETAX MARGIN	The ratio of profit before tax to the net sales
AGE	The foundation year of the firm