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A Smart Approach For Budget Deficits Prediction Under Economic Shocks

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Abstract:
Historically, the main behavior of fiscal policy is to distribute resources, income, and expenditures, which are interconnected functions of economic stability. Recently, the scope of public sector economics has expanded beyond budgetary components in parallel with the development of public finance. While the budget reached the economic division form of budget items based on program and performance theories, Budget monitoring, and financial risk management are currently challenging, particularly in the face of monetary policy uncertainty. Financial institutions are crucially concerned with the stability of public finance in low-income countries (LICs) as it contributes to improved investor confidence and fiscal decision-making. Hence, economists investigated uncertainty shocks and contributed to managing financial risks with global and energy uncertainty indices. Furthermore, the maturity of digital transformation and artificial intelligence financial applications catalyzed scholars to examine its contributions in the fiscal distress prediction field. Hence, this research aims to integrate artificial intelligence into financial performance analysis to bridge the gap in budget forecasting. The study was aimed at proposing an Economics Division Uncertainty approach (EDUA), which combined (ARIMA) and (LSTM) models for time series analysis of Nuclear Material Authority expenditures over the previous five years divided into quarterly periods, to achieve efficiency in spending. The (ARIMA) model's (ADF) results showed that uncertainty indicators are highly significant. The best (p-value) in the first and second differences in (ARIMA) models is (0.0001) for petroleum items, (0.0001) for solar price rates, (0.001) for the US exchange rate, and (0.003) for electricity price rates, when compared to (EDU_LSTM). Both models have similar accuracy rates, with the best being (EDU_ARIMA) (solar price 97%, USD exchange rate 84%). The second study proposed a composite model of four machine-learning tools to enhance financial performance during financial distress. The study collected (12) indicators from general financial literature and corporate studies, utilizing the (XGBOOST, Random Forest, KNN, and Naïve Bayes) models. Comparing the accuracy results for each model presented different accuracy results in the deep learning models over five years of data. The best accuracy score was for Random Forest at (69%), XGBOOT at (68%), and KNN at (68%). We recommended explainable AI as future research to interpret the budget deficit during the fiscal year period.
Keywords: Economic Shocks, Uncertainty, Budget Reliability, Financial Distress Prediction, Artificial Intelligence.

1-Introduction

In the past, fiscal policy encompassed resource allocation, income distribution, and expenditure distribution as interconnected functions of economic stability (Adler, 2021). However, as public finance has evolved into public sector economics, the scope of this field has expanded beyond budgetary components. The distribution of expenditures, like economic events, is dynamic, and government expenditures and resources are divided according to the type of expenditure or revenue and its purpose. Therefore, it is necessary to highlight budget implementation processes to align expenditures within the allocated budget, keep spending below the budget due to income trends below the target, or alert decision-makers to any anomalies and behaviors. Conducting a periodic evaluation of the impact of various policies on public financial indicators. Business-oriented accounting in the public sector, known as management accounting and net budgeting, coordinates management by aims and results. Public accounting regulations are being scrutinized, and reporting procedures have recently gained greater importance in achieving financial recovery (Liapis & Spanos, 2015). Budget reporting involves setting pre-determined aims, reporting actual performance results, and evaluating performance in terms of pre-determined goals (Maheshwari, 2006). Failure to achieve budget goals may cause an organization to be considered ineffective in its multiple roles such as planning, evaluation, coordination, communication, and decision-making (Premchand, 2004). Therefore, budget monitoring has become a necessary process for establishing a spending plan and periodically comparing actual expenditures with that plan to determine whether spending patterns need to be modified to stay on track, control spending, and achieve various financial goals (Dunk, 2009). By implementing a proper budget control plan, a company can reduce costs and improve the quality of its services based on budget allocations. This helps reduce costs and enhance goal achievement and thus organizational effectiveness (Mattheis, 2006). To facilitate effective implementation of budget control, management must define appropriate budget control processes, and this is achieved through planning, monitoring, and evaluation (Badu, 2011).

On the other hand, it has been noted that financial crises and global debt crises have a clear relationship with public sector accounting, as mentioned (ABANYAM & ANGAHAR., 2015). Public sector budget preparation systems are subject to change and development based on the dynamics of public sector management and emerging societal demands. The global financial system has been tested time and time again. Since 2020, which turned out to be a precarious era for public finances, these countries have been exposed to the COVID-19 pandemic, energy and cost of living shocks from 2021, and a spike in interest rates in 2022 (IMF, 2022). Today's globalized market aims to balance energy supply and demand, encompassing petroleum, natural gas, and electricity.10 Rising food and energy prices have had a major impact on governments in almost every country, leading to economic turmoil in some developing countries. Therefore, priority measures to deliver sufficient and timely food and energy assistance include the necessity to identify those most severely hit, as well as the extent to which they have been

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affected. Since sources of public revenues are usually limited, while government agencies' need for public expenditures is constantly increasing, accuracy, fairness, and relative importance are required in preparing estimates of the state's general budget figures. Focusing on the Egyptian economy, the Egyptian financial crisis is an economic crisis that struck Egypt in 2023, which led to the Egyptian government and the Central Bank of Egypt devaluing the pound. During the crisis, the country's debt sustainability declined, with continued foreign exchange shortages in the face of increased external public debt service payments and the absence of measures to boost foreign exchange reserves. Political corruption, chronic food and medicine shortages, business closures, unemployment, declining productivity, tyranny, human rights violations, and blatant economic mismanagement have also contributed to the worsening crisis. The government deficit in Egypt approached 450 billion Egyptian pounds (1.29 billion US dollars) during the first half of 2022-2023. During the period under review, revenues generated by the government were less than government spending, resulting in a fiscal deficit. The Ministry of Finance expected the budget deficit to rise slightly to (7.0%) of GDP this fiscal year from (6.0%) last year (Central Bank of Egypt, 2023). On January 31, 2024, the Egyptian Council of Ministers decided to reduce public treasury funding in the investment plan for the fiscal year 2023-2024 by 15% of the targeted allocations to entities within the state's general budget. The Council of Ministers also indicated that new projects will not be started during the current fiscal year, but priority will be given to projects whose completion rate has reached 70 percent or more, and focus on necessary and urgent investment needs alone, considering adherence to government directives and rationalizing spending, reducing the external debt ceiling, and encouraging production. Local and national industry. This indicates the weak performance of financial planning for Libyan public budgets. Inaccuracy and objectivity of general budget estimates. Failure to adopt modern financial planning principles in preparing and formulating the general budget and its estimates leads to weak efficiency of programs and services, and failure to achieve the desired goals.

With digital transformation, the government can efficiently implement present fiscal policy, improving current practices. it may be possible to design policy in new and innovative ways shortly. The information they have access to, the systems they construct, and the policies they devise and put into effect are all improved. Budgeting cannot be left behind in this transformation because it is one of the most important financial activities of governments (Ayala, 1996; Buchanan, 2014; Dalton, 2013; Gruber, 2005). Without a comprehensive budget, it is challenging to monitor expenses or develop a growth plan. E-government has allowed reforming the functioning of public administrations (OECD, 2003), and digitalization has also affected the budgetary field. In the past twenty years, major multilateral organizations such as the World Bank, the IMF, the Asian Development Bank, the African Development Bank, and the United States Agency for International Development (USAID) have worked on initiatives to modernize public finance management in member countries. Automating Government Financial Management (GFM) Systems, commonly known as Integrated Financial Management

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Information Systems (IFMIS), is an important aspect of this effort. Government finance and accounting staff can benefit from these systems, which involve computer programs, databases, processes, and technology platforms to assist with daily tasks. In this regard, Egypt aims to move towards digital transformation based on the framework of the government's work program and Egypt's vision and key performance indicators for knowledge, innovation, and scientific research until (2030).

Therefore, according to what was mentioned in the literature and explained above, we may summarize the motivation for the research in that it is necessary to have smart mechanisms that help financial management and decision-makers keep up with fluctuating economic events and the ability to analyze financial data in light of the current crises that affect the financial aspect of institutions and finally shed light on budget items, which are affected by uncertain factors that international institutions have classified.

2. State of The Art

2.1 Uncertainty Indices

Today, managing financial risks is a challenge, particularly considering economic policy uncertainty. Multiple tests have been conducted on the global financial system. Since 2020, which turned out to be a very risky era for public finance, they have been hit by the (COVID-19) pandemic, the energy and cost of living shocks from (2021), and the sudden interest rate rise in (2022). Since technology and globalization have transformed society, there has been an increase in the importance and intensity of uncertainty. Political division, polarization, and the increasing role of government spending in the overall economy were the main factors contributing to the recent increase in uncertainty. Thus, numerous scholars who deal with uncertainty shocks have played a significant role in managing financial risks with economic policy uncertainty. They use time series analysis to examine spot-to-future oil prices, energy rate, and currency exchange rates, using a systematic approach during and after the global financial crisis.

Initially, (Baker, Bloom, & Davis, 2016), the first economist to analyze and evaluate policy uncertainty for the United States and 11 other major economies, was involved in developing new measures of economic policy uncertainty. This was a fundamental reference for all subsequent work on the same topic. Their analysis, however, was limited to the link between policy uncertainty and firm-level stock price volatility, investment rates, and employment growth. The data showed that the theories emphasize the negative economic consequences of uncertainty shocks. Takeshi Shinohara (2020) investigated the empirical features of four main indices in the United States and Japan (the Macroeconomic Uncertainty Index, the Economic Surprise Index, the Volatility Index, and the Economic Policy Uncertainty Index). Employing PCA they estimated the time series property of the indices on their developments at each historical economic event. They assessed whether each index explains the macroeconomic fluctuation of investment, durable consumption, and banks' lending attitude relative to their average business cycle. The results show that the Volatility Index rises when the financial system is stressed, and the Economic Policy Uncertainty Index responds to overseas events. The World Uncertainty Index (WUI) is constructed by Hites (Ahir, Bloom, & Furceri, 2022) and uses data from the Economist Intelligence Unit country reports to analyze a panel of 143 individual countries with an imbalanced score. Their goal is to investigate the correlation between uncertainty and output, investment, and productivity by the WUI. The results are broadly in accord with theories and previous empirical studies, which emphasize the negative economic outcomes of uncertainty shocks. It appears that global economic activity may be adversely impacted by the high level of uncertainty in the world, as suggested by the results. In 2023, Spyridon Boikos, Eirini Makantasi, and Theodore Panagiotidis developed a macroeconomic uncertainty index using Google Trends. The index was constructed based on four terms: inflation, unemployment rate, and 10-year government bond yield. They utilized Vector Autoregressive (VAR) models to examine the relationship between their Uncertainty Index and the three variables mentioned earlier. The results showed a positive correlation with The Economic Policy Uncertainty Index (EPU) by Baker and colleagues (2016), as well as The Consumer Confidence Index (CCI) for most Eurozone countries, which was in line with economic theory.

The oil market's significant level of uncertainty has posed challenges for policymakers and investors worldwide (Yang & Webb, 2022). The interconnection between oil and other financial markets has led to a more enduring spillover of oil shocks to other financial markets during the economic shocks, resulting in observed strong volatility in these markets. Tian Gan (2023) and Li Li (2023) explored the impact of oil price uncertainty on the cost of debt by analyzing bonds issued by Chinese firms using regression analysis, finding that oil price uncertainty can increase the bond offering spread, leading to increased debt costs and default risks. Additionally, their counterfactual analysis demonstrated that increased financial stress exacerbates the adverse impact of oil price uncertainty on real economic activities. (Abiad & Qureshi., 2023) study examined the impact of oil price uncertainty on macroeconomic activity, utilizing textual analysis to create a news-based measure of global oil price uncertainty. The study suggested that oil price uncertainty can significantly influence economic fluctuations, proposed policy implications for monetary and fiscal policies, and the transition to clean and renewable energy. (Dang, Nguyen, Lee, Nguyen, & Le., 2023) developed an uncertainty index based on a text-mining algorithm in the energy-related uncertainty context. He devoted this study to the energy field, focusing on 28 countries between developed and developing countries between 1996-2022. The data source was based on monthly reports issued by economic intelligence. After evaluating the proposed index, the study's results showed that the energy uncertainty index may be greatly affected by oil shocks and other crises such as financial crises, the COVID-19 pandemic, etc. Natalia et al. 2024 constructed uncertainty indices associated with metal and energy prices. They used energy price forecasts of six and forecasts for mineral commodities of fourteen prices for the next year. A VAR model was estimated that contains other indicators such as commodity prices, commodity returns, a measure of global activity, a measure of economic uncertainty, and a measure of global financial uncertainty. Finally, the results showed that a positive shock of uncertainty associated with metal or energy prices leads to a significant decline in global financial and economic activities. In the context of uncertainty in global currency prices such as the dollar and the euro, Theodora Permia 2024 conducted an experimental study of the impact of the currency uncertainty index on global commodity prices. This study used commodity futures prices close to the GSCI index, which were retrieved from Datastream for futures prices for daily commodities such as agricultural products, metals, and energy. The study focused on four countries known for exporting basic commodities, namely Australia, Canada, New Zealand, and Norway, and two major importers of basic commodities, such as Korea and Japan. They targeted the actual exchange rate and linked it to the local currency rate, with the dollar and the euro as reference standards. The researchers built a travel model for a quarterly series of the consumer price growth rate, the total export growth rate, and the domestic product growth rate during the period between 1994-2021. Data was collected from the Federal Reserve Bank of St. Louis and International Fund databases. The results showed that the shock of uncertainty in global commodity prices leads to a decline in commodity currencies and the rise in the value of the currency affects foreign investment, which makes some investors expect a recession in global markets. To summarize the above, we may realize that governments must consider the state of uncertainty in commodity prices, especially fuel and energy prices, because market uncertainty shocks may generate varying effects in the short term. Agricultural shocks and metal shocks may lead to a decline in commodity currencies.

2.2 Smart Distress Prediction

Recently, smart early warning for bankruptcy detection has been crucial to detecting problems quickly and putting forward targeted solutions. AI-based bankruptcy detection research indicated that the traditional statistical models were limited and comparable with machine learning integrated models, and at present, machine learning is widely used in fiscal distress prediction, such as (ANN), (DT), (CBR), and (SVM). The machine learning community has always valued risk assessment and portfolio management, which is also applicable to researchers. Nino and others have done a paper on whether it is possible to predict the financial distress faced by municipalities. They created a model that included 7,795 Italian municipalities between 2009-2016 and considered the social and economic characteristics at the municipal level. The methods used are four different algorithms: LASSO (Tibshirani, 1996), Random Forest (Breiman, 2001), Neural Network Venables and Ripley (2002), and Gradient Boosted Machine (Friedman, 2001). The results of the study showed that financial indicators that have characteristics of deficits and municipal debts, such as the ratio of revenues from borrowing to total municipal revenues, the ratio of surplus or deficit to current revenues, and the effect of loan repayment expenses on current revenues, are among the most important indicators that enhance the prediction of financial distress for municipalities. (Halim, Shuhidan, & Sanusi, 2021) presented an experimental study on the credit risks of Malaysian institutions. The study aimed to evaluate the effectiveness of deep learning models in the ability to predict financial deficits. From their point of view, this study may contribute to developing an approach to credit risk assessment, which will greatly benefit researchers, policymakers, and governments. The most important of these models are RNN, LSTM, GRU, and FDP. The content subject to the experiment was sourced from the profiles of 98 public companies listed on the Malaysian Stock Exchange from various sectors such as industrial products, consumer products, and the construction sector, and they were classified under critical status and good status to balance the analysis sample during the period between 2011-2017. The results indicated that all deep learning models achieved 90% accuracy, and therefore the deep learning approach will lead to better performance in financial failure prediction studies. Dan Shin 2021 built a framework for a local government debt risk assessment system. According to their views, government debt risk is the result of many variables working in concert. The proposed framework is based on three criteria: economic situation, revenues, financial exchange, and the status of local government debt. With the use of an analytical hierarchy and entropy approach to the global weight to make the weight calculations more objective, the researcher used the machine learning algorithms BB and CART to implement early warnings about local government debt risks. The results showed that the accuracy of the forecasts reached 85.72%. In the context of forecasting the financial deficit related to energy, Lin Wei 2023 presented two early warning models based on the Bayesian network, the first model is the Bayesian network, and the other is the Bayesian neural network. This study was based on financial risk data during the period between 1987 and 2015 and was divided into two parts, the first part was 25 sets of data that were replaced in the regression, and the second part was 4 sets of data that were tested. The results showed that the Bayesian network has a better forecasting effect than the Bayesian neural network, with an effect of 80%. Therefore, the researchers proposed using virtual networks to predict the financial risks of energy in the context of the financial and governmental sectors. In recent years, both academic and industrial disciplines have paid close attention to text mining in the financial field. This is because text mining is an excellent method for analyzing financial markets or economic events. Li Shan 2021 presented a study on financial risk prediction by constructing a domain sentiment lexicon and conducting sentiment analysis for financial risk prediction. This dictionary consists of three main elements: data preprocessing, which focuses on creating a set of sentiment words in the field of financial risks, a word vector model, which calculates the similarity of words in the initial set of words in the financial field set through Word2Vec and the BERT model, and finally building a classifier based on deep learning, such as DNN, MA-DNN based on multi-head attention, , and bidirectional long-term memory (Bi-LSTM). The data was collected from 214 listed companies in China that obtained the ST mark between 2012-2018, and through

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Python, the SVM, DT, XGboost, and DNN algorithms were applied. The results of the study showed that the highest accuracy rate was for the DNN algorithm with an injection rate of 85.71%, followed by the XGBoost algorithm with a percentage of 85.03%, from which they concluded that sentiment features may achieve satisfactory predictive performance in the field of financial risks.

This research is aimed at providing a systematic analysis of financial data from different sources and determining the efficiency of machine learning and deep learning in improving financial decisions with uncertainty. This goal has been broken down into multiple objectives, one of which involves presenting a proposed model that includes potential scenarios. During the planning phase for the local budgetary system, use time series forecasting to estimate quarterly expenditures. Secondly, utilize regression analysis to keep track of real-time fiscal activities in emerging markets and developing economies. Third, conduct a study on distress prediction using various machine-learning algorithms that are employed in popular predictive fiscal performance studies. This is the inaugural study that applies this methodology to a budgetary system. As a flexible framework that focuses primarily on accurate predictions, this article is organized as follows: the next section will review the details of the materials and method that will be employed in this research; Section 3 presents an experimental approach that involves conducting a process of data gathering and analysis; Section 4 presents empirical findings and their discussion; and the concluding remarks are given in the last section.

3. Material and Methods

Quarterly and annual financial statements for a specific period are created in financial accounting, including *(Balance Sheets*, *Income Statements*, and *Cash Flow Statements)* (Chakri, Pratap, Lakshay, & Gouda, 2023). Thus, analysts acknowledge financial statements (*FSs*) are standardized and dependable sources of information for investors, regulators, financial analysts, and others to make economic judgments about a company's financial condition, performance, and changes. They tried to benchmark the deficit in the country's budget, and they mentioned that the most critical point is budgetary transparency, which makes the budget more transparent and assists in monitoring critical national projects or initiatives (IMF PFM Blog, 2024). Therefore, as shown in Figure 1, we suggest two scenarios for budget credibility at uncertain and risky times. The first proposal of the budget department is to estimate future expenditures to strengthen its policy plan. The budget department bases this entirely on a quantitative approach, using secondary data from the MoF Relational Database as a documentary source. We suggest additional external data sources based on section (2.1), such as official online newspapers, to explore recent exchange and energy rates for the second proposition. Managers can use these sources to gauge the impact of energy price changes. These analytical studies should have focused on budget items linked to market prices. Then, we can easily detect the financial deficit at the budget item level and predict it using deep learning techniques, which we will elaborate on in the following sections.

As previously stated, in line with the Ministry of Electricity, Energy, and Renewable Energy's strategy to raise the proportion of renewable energy in the total energy generated to (42%) by (2035), several agreements have been made to invest (416 billion) Egyptian pounds. However, the details of these agreements remain undisclosed. Regarding wind energy, as of (June 30, 2022, the total capacity of wind farms was (1,633 Megawatts), an increase from around (1,385 megawatts) on (June 30, 2021). The overall combined generating capacity of solar and thermal energy for solar energy projects in the (*Benban*) region during the years (2021–2022) was (140 Megawatts). photovoltaic solar components generated (20 Megawatts) of this total. Additionally, the total capacity of solar energy employing photovoltaic cells was (1465 Megawatts) out of a total capacity of (1491 Megawatts). The Nuclear Materials Authority approved the establishment of the Egyptian Black Sands Company and approved its economic feasibility study. The company has a capital of 500 million Egyptian pounds. A study by (Kadim, Sunardi, & Husain, 2020) emphasized that there is a need to decrease the trade balance deficit by enhancing Egyptian exports to promote economic growth. Thus, it is essential to fulfill a crucial and certain function to validate the feasibility of attaining objectives via competitive market processes. Experts acknowledged the significance of mining and separating black sand for the growth and prosperity of commercial and strategic locations. Utilizing the separation and processing process improves the trade balance, boosts exports, promotes domestic industries, and optimizes arrangements to facilitate export growth. The Nuclear Materials Authority is a crucial entity that plays a significant role in accomplishing the objectives of the Ministry of Electricity and Renewable Energy. It actively contributes to national projects that are under the administrative and financial supervision of the Ministry of Electricity and Renewable Energy. This study will predict the expenses and revenues of the Nuclear Materials Authority, and the data extraction process depends on the data on the expenditures and revenues of the Nuclear Materials Authority balance sheets from (June 2019 to June 2023).

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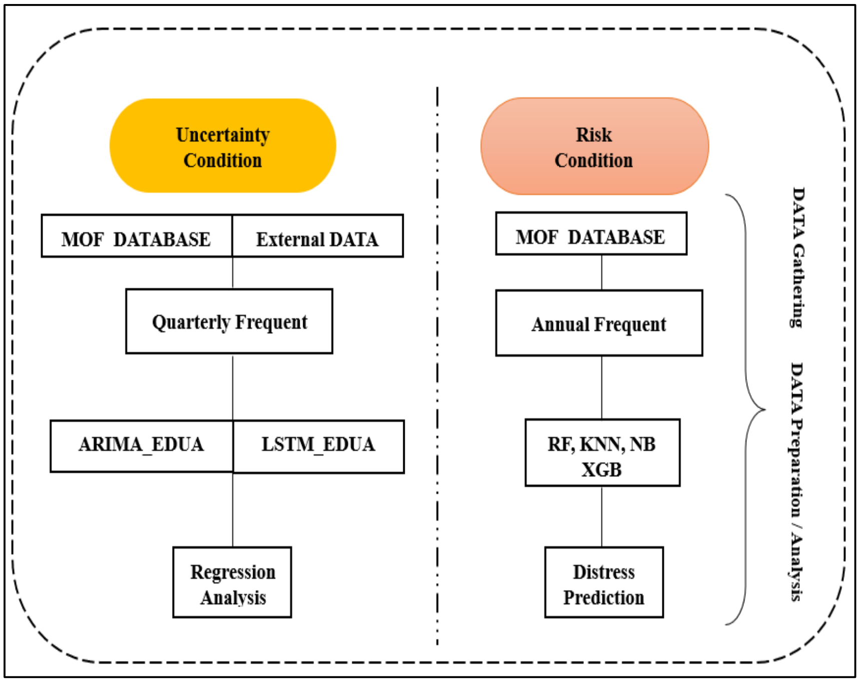

FIGURE 1 RESEARCH FRAMEWORK

3.1 DATA

The Ministry of Finance (GFMIS) database provided the data for this study. The GFMIS produces reports on daily transactions posted to the ledger, which is the daily calculation. Monthly and annual reports, such as financial statements and balance sheets, include the annual report, which includes cash flows and final accounts covering 2019–2023. We retrieved the variables related to the acquisition of goods and services, non-financial assets (investments), and resource and capital income indicators. This is common to all observed periods. Finally, the indicators related to the authority's financial performance were used to form exploratory variables by calculating the percentage changes of each economic indicator during one of the three proposed time intervals; therefore, the calculation periods might be the following: quarter-based for time series analysis and annual-based for scenario regression and fiscal performance analysis. Therefore, to analyze the budget's credibility and financial performance, we will focus on the budget items related to the expenditure component. Therefore, we have selected some crucial elements, such as the exchange rate and energy price *(Diesel, Electricity)*, based on the economic division of the budget items and their connection to prices. These elements are listed under the item *(Goods and Services)* and the item *(Investment)* financial ratios are widely used to estimate model parameters. Financial ratios are used in nature to assess an institution's financial performance. These ratios are typically calculated based on quarterly or annual financial data.

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Financial reports, including balance sheets, profit and loss accounts, and income statements, are the source of financial ratios. Since financial ratio statistics generally fluctuate over time and in response to changing conditions, we refer to this data as time series data. We summarize almost all financial ratios that are mentioned in the literature on fiscal performance and distress prediction. Furthermore, we noticed that fiscal ratios cover seven critical performance categories: (*profitability, solvency, operational capacity, growth capacity, cash liquidity, structural ratio, and per-share ratios)*. It is also critical that the material expressed by these financial aspects is diverse, as many financial indicators are overly repetitive. In the financial distress prediction state, our early indicators are based on a combination of preliminary indicators proposed in several research projects on FDP. Table 1 summarizes the chosen 12 financial indicators from three categories: Budget Reliability, Liquidity, and Leverage or Debt Ratios.

In Table 1, Budget Reliability reflects the realistic extent of the budget by comparing actual expenditures and revenues with the original budget. The reliability criterion includes three types: *(Aggregate Expenditure Outturn),* which reflects the extent to which total budget spending exceeds the initially approved amount as defined in government budget documents and financial reports; *(Expenditure Composition Outcome),* which reflects the extent to which reallocations among major budget categories during implementation contribute to variation in the composition of expenditures and the use of emergency reserves; and *(Revenue Outturn),* which indicates the change in revenues between the original approved budget and the year-end output. Various financial ratios, such as liquidity, leverage, and debt ratios, have been defined and studied in the literature. An institution's (*liquidity ratio)* is considered one of the most crucial financial measures, as it assesses its ability to meet short-term financial obligations based on current assets. The (*current ratio*, *working capital to total assets ratio, quick ratio*, and *cash ratio)* are all ratios that evaluate the ability to convert current assets into cash. On the other hand, the *(Debt Ratio)* determines the proportion of a company's debt-financed assets, and the *(Capital-to-Net-Worth Ratio)* gauges the amount of debt and equity utilized by a corporation to fund its activities.

TABLE 1 SELECTED PERFORMANCE INDICATORS

Category	***Ratio***	***Calculation***	***Index Code***	***Citation***
Budget Reliability	*Aggregate Expenditures Outturn*	*AEO = OB/MB*	*Rev-Exp-OB/MB*	[25], [26]

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	Expenditures Composition Outturn	*ECO = OB/Ac*	*Rev-Exp-OB/FA*	
	Revenues Outturn	*RO = MB/Ac*	*Rev-Exp-MB/FA*	
Liquidity Ratios	*Current Ratio*	*Current Assets/Current Liabilities*	*CUR*	[27],[28],[29],[30],[31]
	Working Capital to Total Assets	*Working Capital /Total Assets*	*WOC*	
	Quick Ratio	*Liquid Assets /Current Liabilities*	*QR*	
	Cash Ratio	*Cash + Cash Equivalents / Current Liabilities*	*CAR*	
Leverage or Debt Ratios	*Debt Ratio*	*Total debts /Total assets*	*DR*	
	The Ratio of Capital Employed to Net Worth	*Capital Employed/ Net Worth*	*CENW*	

3.2 Methods

At the level of senior management of the institutions, managers may face some challenges in estimating the financial ability to adhere to the monthly and annual expenses, as well as estimating the annual planned revenues. Recently, they found practical issues that reflect the impact of uncertainty indices such as exchange rates and energy rates on expenditures. Therefore, it is necessary to find intelligent solutions that can enhance financial decision-making by predicting the results of economic fluctuations. Hence, in this study, we suggest multiple experimental studies in the style of the study's objective. To overcome the problems of financial deficits and reduce the severity of financial crises. The first is using time series analysis of expenditures and revenues using the most important statistical tools, such as *(ARIMA and LSTM)*, to obtain the most accurate results. While the most vital scenarios in this study are due to its interaction with economic changes, which significantly affect the costs of the Authority's

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projects, we will analyze the impact of the dollar price and the price of petroleum products on invested assets, goods, and services. Finally, it installs an intelligent model that relies on several sub-tools of artificial intelligence, such as *(Random Forest, Naïve Byas, K Nearest Neighbor, and XGBOOST),* for classifying and evaluating the most important financial indicators that reflect the financial performance of the Nuclear Materials Authority.

ARIMA

ARIMA, also known as the Box-Jenkins model is a time series analysis that builds a model to forecast future data values using past data (Olah, 2015). Usually, an *ARIMA* model contains three parts the *Auto-Regressive (AR), Moving Average (MA),* and *One-Stop Differencing Algorithms.* The current sample is calculated as a symmetrical weighted sum of past samples of the (AR) component, and the (MA) component is used to identify the correlation between prediction errors, while the one-step differencing component records the connection of adjacent samples.

The general model for ARIMA (p, d, q) is expressed as:

$$(1-\varphi 1\beta-\varphi 2\beta 2-\cdots.-\varphi\rho\beta\rho)(1-\beta)d\gamma\tau=90+(1-\theta 1\beta-\theta 2\beta 2-\cdots\ldots-\theta q\beta)\epsilon\tau \quad (1)$$

The *ARIMA (p,d,q)* is expressed as :

$$\varphi(\beta)\gamma\tau=\varphi(\beta)(1-\beta)d\gamma\tau=\ \theta(\beta)\in\tau \qquad (2)$$

where $\varphi(\beta)=(1-\varphi 1\beta-\varphi 2\beta 2-\cdots.-\ldots.-\varphi\rho\beta\rho,\theta(\beta)=1-\theta 1\beta-\theta 2\beta 2-\cdots\ldots-\theta q\beta q,$

d of differencing and $\in\tau$ is a series of irrational mistakes with constant variance and no mean $\sigma 2$. Model *(2)* for the series $\gamma\tau$ is denoted by *ARIMA (p,d,q)*. The degree parameters (φ) and (θ) are selected so that the zeros of both polynomials are positioned outside the unit circle, preventing the generation of unbounded processes.

LSTM

A popular recurrent neural network *(RNN)* design in Deep Learning is *(LSTM)*. It is perfect for sequence prediction jobs because it captures long-term dependencies. Long short-term memory *(LSTM)* neural networks can handle whole data sequences rather than individual data points because they use feedback connections. Time series, text, and voice are all examples of sequential data, making it excellent at analyzing and forecasting patterns. Three components make up the *(LSTM)* network design. The term for these components of an *(LSTM)* unit is gates. Memory cells, also known as *(LSTM)* cells, rely on them to regulate the incoming and outgoing data. Each logic circuit has three gates: the Forget, the Input, and the Output gates. A hidden

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layer and current state for each neuron in a traditional feedforward neural network are comparable to the three gates and *(LSTM)* cells that make up a neuronal layer in an *(LSTM)* unit [33].

Forget Gate: This gate typically employs a sigmoid function when deciding what data to erase from the *(LSTM)* memory. This ($h\tau$- 1), and ($\chi\tau$) is the basis of this choice. The value between *0* and *1*, where one means keeping the whole value and 0 means erasing it, is the output of this gate, denoted as *(Fτ).* We calculate this result as:

$$\mathcal{F}\tau = \sigma(\omega\mathcal{F}h[h\tau - 1], \omega\mathcal{F}\chi[\chi\tau], b\mathcal{F}) \qquad (3)$$

Where ($b\mathcal{F}$) is a constant called the bias value.

The input gate adds new information through two layers, "sigmoid" and "tanh," and their results are calculated using the following equation:

$$\mathcal{I}\tau = \sigma(Wih[ht\text{-}1], wix[xt], bi) \quad (4)$$

$$\tilde{C}\tau = tanh(Wch[ht\text{-}1], Wcx[xt], bc) \quad (5)$$

Equations No. 4 and 5 represent whether there is a need to update the current value, ($\tilde{C}\tau$), indicating new values that are candidates to be added to the LSTM memory. The current value is canceled using the forget gate, then multiplied by the previous value (i.e., Cτ-1), and the new value is added to ($\tilde{C}\tau$) through the following equation:

$$C\tau = \mathcal{F}\tau * C\tau - 1 + \mathcal{I}\tau * \tilde{C}\tau \quad (6)$$

Where $\mathcal{F}\tau$ is the result of Equation (3), and its value lies between 0 and 1, where 0 indicates the total deletion of the value and 1 indicates its preservation.

The output gate determines the part that will contribute to the output process from the LSTM memory and is represented by the following equations:

$$\mathcal{O}t = \sigma(Woh[ht\text{-}1], Wox[xt], bo) \quad (7)$$

$$ht = \mathcal{O}t * tan\,h(C\tau) \qquad (8)$$

Where $\mathcal{O}t$ is the output value, and ht is its representation as a value between *-1* and *1*.

Random Forest

Random forests are an ensemble learning algorithm used for tasks like Classification and regression. They work by creating many decision trees during the training phase. According to (Breiman, 2001) Random Forests was introduced by Leo Breiman, whom earlier work by (Amit & Geman, 1997) inspired. more formally, for (p) dimensional we have a random vector $\chi = (\chi 1, \dots, \chi\rho)^{T}$ representing the real-valued input or predictor variables, and random variable Y

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representing the response variable with absolute values. We assume that there is an unknown joint distribution ($P_{\chi\Upsilon}$ (χ, Υ)) for $(\chi) and$ (Υ). The objective is to develop a prediction function $\mathcal{F}(\chi)$ to forecast (Υ) accurately. The prediction function is determined by a loss function $L\ (Y, \mathcal{F}(\chi))$ and is designed to minimize the predicted value of the loss.

$$E_{\chi\Upsilon}(L(Y,\mathcal{F}(\chi))) \quad (9)$$

The subscripts indicate the expected value concerning the joint distribution of χ and Y. L (Y, $\mathcal{F}(\chi)$) may be seen as a metric that quantifies the proximity between $\mathcal{F}(\chi)$ and Y. It imposes a penalty on the values of $\mathcal{F}(\chi)$ that deviate significantly from (Y). Common options for L include squared error loss.

$$L(Y,F(X)) =(Y - F(X)) \quad (10)$$

k-Nearest Neighbor

The core concept of Nearest Neighbor Classification is relatively simple: instances are categorized according to the class of their closest neighbors. Considering many neighbors has been often advantageous. Therefore, the method is called k-nearest neighbor *(k-NN)* Classification, in which the class is determined using the k closest neighbors. Memory-based Classification is a term used to describe the necessity for training samples to be present in memory during runtime. The approach is classified as Lazy Learning since the induction process is postponed until runtime. We assume to have a training dataset (D) comprising *(Xi)* I$\in[1, |D|]$ training samples.

The examples are described by a set of features *(F)*, and any numeric features have been normalized to the range [0,1]. Each training example is labeled with a class label ($\mathrm{Y}_i \in Y$). Our objective is to classify an unknown example (*q*). fForeach (*Xi* $\in$ *D)*, we can calculate the distance between (*q*) and *(Xi)* as follows:

$$d(q,Xi) = \sum_{\mathcal{F}\in \mathrm{F}} \omega\mathcal{F}\delta \ \ Xf\in F\ \delta(qf, Xif) \ (11)$$

An optimal strategy is to designate the predominant category among the closest neighbors as the assignment for the query. Assigning more weight to the closest neighbors when determining the class of the query is generally a logical choice. A practical and versatile approach to do this is by distance-weighted voting. In this strategy, the neighboring instances contribute to the Classification of the query instance by casting votes that are weighted based on the inverse of their distance from the query.

$$V\ ote(\Upsilon i) = \sum_{C=1}^{K} \frac{1}{d(q,Xc)^{\ 2}} 1(\Upsilon\iota, \Upsilon c) \quad (12)$$

Naïve Byas

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In statistics, *Naive Bayes* classifiers are a type of probabilistic classifier used in statistics. They assume that the features are conditionally independent, given the target class, hence the name "naive". They are simple Bayesian network models and are highly scalable. In *Naive Bayes* [38] define:

- ***C*** as a variable that randomly represents the class of an instance.
- ***X*** (X_1, X_2, X_k) as an array of random variables that represent the observed attribute values.
- ***c*** as a particular class label.
- ***x*** *(x1, x2,...,xk)* as a particular attribute value vector that has been observed.

Training data evidence is used to help the learner predict a test instance for x's class. By choosing a $argmax_{\mathcal{C}}(\mathcal{P}\ (\mathcal{C} = c|\mathcal{X} = x))$ for each x, the expected classification error can be minimized. Bayes theorem can be used to calculate:

$$P\ (\mathcal{C} = c|\mathcal{X} = x) = \frac{P(\mathrm{C}=c)P(\mathcal{X}=x|\mathrm{C}=c)}{P(\mathcal{X}=x)} \quad (13)$$

Since the denominator in (13) is invariant across classes, no effect on the final choice and it’s dropped:

$$P(\mathcal{C} = c|\mathcal{X} = x) \propto P(\mathrm{C}= c)P(\mathcal{X} = x|\mathrm{C}= c) \quad (14)$$

The training data must be utilized to estimate the probabilities of $P(\mathrm{C}= c)\ and\ P(\mathcal{X} = x|\mathrm{C}= c)$. Unfortunately, estimating $P(\mathcal{X} = x|\mathrm{C}= c)$ may not be directly possible because *(x)* is an unseen instance that is not in the training data. so a simplification is made: if attributes *($\mathcal{X}1, \mathcal{X}2,..., \mathcal{X}k$)* are conditionally independent of each other given the class, then: $P(\mathcal{X} = x|\mathrm{C}= c) =$

$$P(\wedge_{\mathrm{i}=1}^{K}\ \mathcal{X}\mathrm{i} = x\mathrm{i}|\mathrm{C}= c)$$

$$= \prod_{\mathrm{i}=1}^{K}\ P(\mathcal{X}\mathrm{i} = x\mathrm{i}|\mathrm{C}= c) \quad (15)$$

Combining (14) and (15), one can further estimate the most probable class by using:

$$P(\mathcal{C} = c|\mathcal{X} = x) \propto P(\mathrm{C}= c)\prod_{\mathrm{i}=1}^{K}\ P(\mathcal{X}\mathrm{i} = x\mathrm{i}|\mathrm{C}= c) \quad (16)$$

Classifiers using (16) are naive Bayes classifiers. Several studies suggest that creating an ensemble model based on a specific case is necessary as no single classifier produces the best results in all cases. probability P$(\mathcal{C} = c|\mathcal{X} = x)$ denotes the conditional probability of a class c given an instance x. The probability p(C=c) denotes the prior probability of a particular class c. The probability P$(\mathcal{X}\mathrm{i} = x\mathrm{i}|\mathrm{C}= c)$ denotes the conditional probability that an attribute $\mathcal{X}\mathrm{i}$ takes a particular value $x\mathrm{i}$ given the class c.

XGBoost

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Boosting algorithms iteratively combine weak learners, marginally better than random learners, to create strong learners. Gradient boosting is a regression approach that resembles boosting [40]. Given a training dataset $\mathcal{D} = \{\mathrm{Xi}, \Upsilon\mathrm{i}\}_1^{\mathcal{N}}$. The objective of gradient boosting is to discover an approximation, $\widehat{\mathrm{F}}(x)$, of the function $\mathrm{F}^*(x)$, which maps instances x to their output values y; by minimizing the expected value of an expected loss function. $\mathcal{L}(\gamma, \mathrm{F}(x))$. Gradient boosting constructs an additional estimation of $\mathrm{F}^*(x)$ by combining a series of functions.

$$\mathcal{F}_m(\mathrm{x}) = \mathcal{F}_{m-1}(\mathrm{x}) + \mathcal{P}_m \mathrm{h}_m(\mathrm{x}) \quad (17)$$

Where $\mathcal{P}_m$ is the weight assigned to the m^{th} function, $h_m(x)$ the ensemble comprises these functions, such as decision trees, which serve as the models. One machine learning approach that uses gradient boosting to create an ensemble of decision trees is (*XGBOOST)*. Its scalability is greatly enhanced by this method. Minimizing a loss function, *(XGBOOST)* is like gradient boosting, and generates an objective function that is additively expanded. While other boosting techniques employ a variety of base classifiers, (*XGBOOST)* only uses decision trees. To manage the trees' level of complexity, a variant of the loss function is used.

$$\mathcal{L}_{xgb} = \sum_{i=1}^{\mathcal{N}} \mathcal{L}(\mathcal{Y}i, \mathcal{F}(xi)) + \sum_{m=1}^{m} \Omega(h_m) \quad (18)$$

$$\Omega(h) = \gamma \mathrm{T} + \frac{1}{2}\lambda \parallel \omega \parallel^2 \quad (19)$$

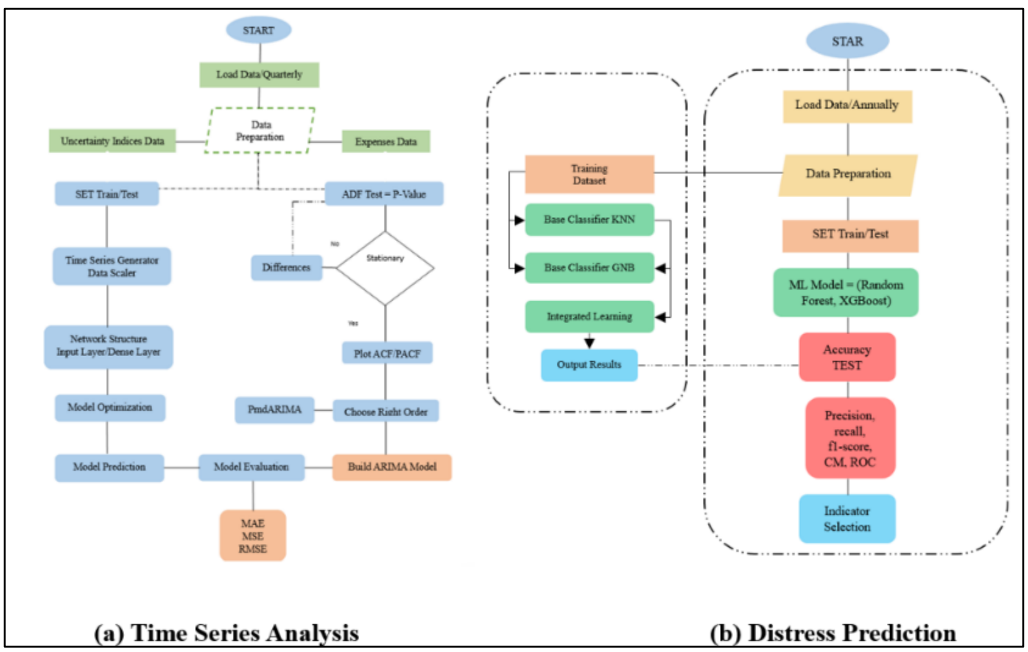

FIGURE 2 RESEARCH PROCESS FLOWCHART

In this case, (ω) represents the output scores of the leaves and (T) represents the number of leaves in the tree. By incorporating this loss function into the split criteria of the decision tree, a

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pre-pruning technique that uses a larger value of (γ) produces trees with less complexity. A minimal loss reduction gain required to separate an internal node is the value of (γ) controls.

4. Preparing for the Experiment

This study aims to enhance fiscal decisions in uncertainty and risk conditions by creating a framework that estimates the financial performance measures of financial sectors listed in the Ministry of Electricity and Renewable Energy. The Ministry's goal is to optimize the use of available energy sources taking into consideration environmental protection and expand the utilization of new and renewable energy resources. Hence, we split the research process into two main flowcharts. First, as shown in Fig2(a) we suggest predicting the effect of the (*USD*) exchange rate and (*Energy*) price rate on expenses using the suggested approach (EDUA) to determine which item listed in the budget may affected by uncertainty indices by Linear Regression analysis, then Time series analysis by *(ARIMA and LSTM)* employed to predict estimated expenses of selected items and uncertainty indices.
Second, in this case, we will list a budget item into risk item (0) and non-risk item (1). In this case, we will list the budget items as a risky item (0) and a non-risky item (1). The risk item is characterized by a financial deficit and affects the performance of the accounting unit in paying its obligations. However, the non-risk item is characterized by the presence of a surplus in it and may enhance other items that have a deficit, and from here it may enhance the performance of the accounting unit. To determine the credibility of affiliated authorizes a constructed model employing machine learning techniques to predict performance ratios. Several studies have argued that the ensemble model generated better results than a single classifier in all cases. The proposed base classifiers include *(KNN and Naïve Byas),* initially. From popular integration techniques like *(XGBOOST and Random Forest),* the one that works best in this scenario is selected. To make the most of the ensemble, we use an aggregate function ensemble model for everything from indicator selection to classifier generation. Figure 2(b) shows the process ensemble model's flow diagram. There are two sections of the diagram: (i) choosing indicators and (ii) building classifiers. For the experimental section, we'll be using *(Python's Scikit-learn)* and *(Keras)* frameworks for machine learning. The platform for developing algorithms is *(Jupyter Notebook).* While *(Keras)* offers a high-level neural networks API, and *(Scikit-learn)* is a Python package that incorporates numerous machine-learning methods.

4.1 Data Preparation: The collected data has been saved in Comma-Separated Values *(CSV file format)* and it's divided into two sets.

a) The first dataset is a collection of time series data split into quarterly intervals spanning five years, In the Regression Analysis we will use the *(EDUA)* Economic Division uncertainty approach, while the Ministry of Finance has classified the general revenues and expenditures in an economic classification. There are two ways to classify expenses. The first is based on economic spending, which divides expenses into those for goods and services and those for investment assets. The second is based on external factors, such as the *(USD)* exchange rate and *(Energy)* price rate**.**

b) The second dataset is divided into a yearly form. The next step is to load the data into memory, followed by data preprocessing, which focuses on data cleaning. Columns containing less than 100 occurrences will be included in the dataset. The data that has been cleaned will be divided into two sets, one for training and one for testing. The ratio of the real dataset to the projected dataset will be (70:30). Additional information will be elaborated upon in the following sections.

4.2 Model Optimization Multiple models are created individually During the model optimization phase.

a) For the *(ARIMA)* model we employ the *(SARIMA)* model to allow data to be differentiated based on seasonal and non-seasonal frequencies. Determining optimal parameters can be simplified using automated parameter search frameworks such as *(Pmdarima)* optimizer to fill the void in Python's time series analysis capabilities. In the deep learning model (LSTM), In *(LSTM)*, we employ *(a Timeseriesgenerator)* to automatically transform both univariate and multivariate time series data into samples, also *(Minmaxscaler)* scales and translate each feature individually such that it is in the given range of the training SEt. The existing *(KERAS)* library with *(ADAM's)* optimizer parameters is used.

b) Secondly in Random Forest we utilize Bayesian Optimization for refining a *(Random Forest)* model on the wine quality dataset, in *(XGBOOST)* we use *(RandomizedSearchCV)* for hyperparameter tuning *(KNN, Naïve Byas)*, and the existing *(SKIRLIT)* library with default parameters skipping the hyperparameter tuning step.

4.3 Model Evaluation to achieve the best possible model performance.

a) The accuracy of time series forecasts will be measured using *(MAPE, MSE, and RMSE)*. Also, the *(Accuracy, Precision, Recall, and f1-score)* are performance metrics [44], which will evaluate the predicted Classification against the actual classification. The mean absolute percentage error *(MAPE)* is a measurement of the average magnitude of error produced by a model, or the average deviation in predictions. The Mean Squared Error *(MSE)* is a statistical measure that quantifies the average of the squared differences between the actual and anticipated values within a given dataset. It quantifies the dispersion of the residuals. The Root Mean Squared Error *(RMSE)* is the mathematical operation of taking the square root of the Mean Squared Error *(MSE)*. It calculates the standard deviation of the differences between observed and predicted values.

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}|\gamma i - \hat{\gamma}| \quad (20)$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(\gamma i - \hat{\gamma})^2 \quad (21)$$

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\gamma i - \hat{\gamma})^2} \quad (22)$$

Where $\hat{\gamma}$ $-$ *Predicted value of* γ

$\bar{\gamma}$ $-$ *Mean value of* γ

b) The key performance metrics for the distress prediction model are *(Accuracy, Recall, Precision, and F-Measure). (Accuracy)* refers to the percentage of true predictions made by a model when applied to a given data set. *(Recall)*, also known as Sensitivity in the field of Psychology, refers to the ratio of accurately predicted positive instances to the total number of real positive cases. This metric quantifies the extent to which the *+P (Predicted Positive)* rule accurately identifies the actual positive situations [44].

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (23)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (24)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (25)$$

$$\text{F-measure} = 2.\frac{\text{PrecisionRecal}}{\text{Precision+Recall}} \quad (26)$$

On the other hand, *(Precision)* or Confidence (referred to as Confidence in Data Mining) is the ratio of accurately identified Real Positives to the total number of Predicted Positive instances. Machine Learning, Data Mining, and Information Retrieval prioritize this aspect, but *(ROC)* analysis fails to address it. Alternatively, it may be referred to as True Positive Accuracy *(TPA)*, which measures the accuracy of Predicted Positives compared to the rate of discovering Real Positives *(TPR)*. The F1 measure is a statistical metric that quantifies the agreement between the True Positives and the average of the Predicted Positives and Real Positives. It is a normalized rate that is expressed as a Proportion of Specific Agreement in statistics. Specifically, when applied to the Positive Class, it is referred to as PS.

5. Results and Discussion

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5.1 Economic Division Uncertainty Approach (EDUA)

The objective of this part is to assist financial management in preventing budget deficits and enhancing the efficiency of budget surplus control. Hence, we provide a model that integrates the components of uncertainty with the budgetary items influenced by these components. Initially, we provide a general overview of the uncertainty indicators by examining the pertinent subjects and devising our methodology for measuring uncertainty that aligns with the data at our disposal. (Konstantinos, 2021). (Caldara & Iacoviello., 2018) have also highlighted the considerable focus that researchers and policymakers have placed on the uncertainties surrounding the years *(2023-2024).* The notion of economic policy uncertainty *(EPU)* was originated and presented by Becker, and subsequently expanded upon with various other indices, such as the Climate Policy Uncertainty Index *(CPU)*, the Geopolitical Risk Index *(GPR)*, and the Global Uncertainty Index *(WUI)*. These indices have sparked empirical investigations into the impacts of uncertainty indicators on economic choices and actions. (Houssin, 2007) Established a connection between their *(EPU)* index and variations in economic uncertainty that are linked to policy decisions. This indicates a deterioration in the overall economic performance of significant economies. This newly developed index specifically targets the growing Economic Policy Uncertainty *(EPU)*, the escalating fluctuations in the market, and the decreasing rate of economic growth. The system was constructed using diverse news sources, with the graphical user interface (GUI) relying on national reports from the Economist Intelligence Unit *(EIU)*. These reports were standardized in terms of their format, the production process, and coverage of various topics.

Furthermore, the economic allocation of the state's overall budget involves categorizing the government's expenses and resources based on the nature of spending or revenue and its intended use. This entails dividing public spending based on its purposes, such as wages, goods procurement, or loan repayment, and dividing public resources based on the classification of their sources, such as taxes, grants, or other forms of income. Inside the economic framework, each primary section (about utilization and resources) has several categories, with each category further including many subcategories, and each subcategory containing various kinds and subdivisions. This detail tries to minimize government spending to enhance oversight of government expenditures. To streamline the management of economic classification and automate the procedures involved in creating and executing the government's overall budget, both public expenditures and public revenues have been assigned specific codes based on their economic classification. Each area of the classification provides further subcategories and items inside it. The many classifications and divisions of a certain code. The primary divisions are shown on both sides of the resources and are used as illustrated in the following table:

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TABLE 2 ECONOMIC DIVISION ITEMS

Item	Economic Code	Year 2019	2020	2021	2022	2023
		Deficit and Surplus Results				
Electricity (E)	**21210204**	**21.92%**	**-6%**	**0%**	**18%**	**68%**
Petroleum and Gas Materials (PGM)	**21210301**	**22.13%**	**22%**	**-12%**	**5%**	**-57%**
Decorations	**21610108**	**5.43%**	**12%**	**0%**	**-6%**	**-5%**
Tools	**21610102**	**30%**	**30%**	**-3%**	**-1%**	**0%**
Machinery	**21610106**	**84%**	**84%**	**-60%**	**-43%**	**64%**
Maintenance of Machinery	**21220105**	**2.67%**	**7%**	**-25%**	**8%**	**-17%**
Transportation	**21610105**	**1.07%**	**13%**	**-2%**	**13%**	**-16%**
Means of Transportation	**21610204**	**45.11%**	**216%**	**-40%**	**-39%**	**3%**
Research for Investment Projects	**21630103**	**-24%**	**73%**	**-9%**	**-25%**	**8%**

By way of contrast, according to the more traditional theoretical view, asset price changes are assumed to influence real economic activity in two ways. Firstly, asset prices are assumed to induce alterations in aggregate demand via wealth and cost of capital effects. Secondly, asset prices are assumed to influence the degree of financial stability and the state of current financial distress by determining whether existing financial constraints (net worth and liquidity constraints) are fulfilled or not, influencing on the one hand potential output by deciding upon whether an economic entity is bankrupt or not, and on the other hand aggregate demand by determining the creditworthiness of borrowers, i.e. The availability of external funds, and there through the maximum number of expenditures. Owing to this traditional view, both spurious and systemic financial crises, as defined above, are possible events to occur, firstly, due to the existence of various transmission mechanisms between the financial and the real sector, and secondly, due to the influence of asset prices on aggregate financial stability. Statistical modeling involves regression analysis, which is a set of statistical processes used to estimate the relationship between a dependent variable (also known as the 'outcome' or 'response' variable, or a 'label' in machine learning terms) and one or more independent variables (also known as 'predictors,' 'covariates,' 'explanatory variables,' or 'features'). In other words, the results of the regression analysis of expenditure items divided based on the *(EDU)* approach to economic classification show the extent to which uncertainty factors affect these items.

First, the case of energy prices such as petroleum products and electricity, as in Figure 3. (a) and Figure 3. (b) Express increased spending on these two issues. Both items, but only slightly, indicate the urgent need for energy to operate the targeted projects. In the case of the dollar price, we find the machinery item, which expresses the costs of drilling and drilling tools, as shown in Figure 3 (c). We may find that the expenses related to this item have decreased due to the impact of these works on the pandemic known as the *(COVID-19)* pandemic, as well as adherence to instructions from the Council of Ministers considering rationalization of spending and economic reform. On the contrary, in the case of Figure 3 (d), the increase in spending is expressed on the transportation item, which contains the costs of purchasing cars and their spare parts, and the research item shown in Figure (e), which contains the costs of scientific research that serves the Authority's projects, which indicates the difficulty of rationalizing Spending on these two items and the urgent need for these products.

5.2 Results of EDUA_ARIMA

Numerous researchers have explored both linear and nonlinear methods for time series prediction. Linear models, such as autoregression *(AR)*, autoregressive moving average *(ARMA)*, autoregressive integrated moving average *(ARIMA)*, and others, are commonly studied. When choosing an appropriate model for a time series, one must first analyze the characteristics of both the series and the model. Three key factors that significantly impact time series modeling are the *(Short-Term Autocorrelation)* of sequences, the *(Fit Selection)* of a linear model, and the *(Check Stationary)* of data sequences. The modeling process for *(EDUA_ARIMA)* is illustrated in Fig (5). After the differencing operation, the *(Stationarity)* of the time series is tested, and the differencing order *(d)* is determined. Based on the sequences, the optimal autocorrelation coefficient *(p)* and the partial correlation coefficient *(q)* are selected. It's important to analyze the *(Stationarity)* of the sequences during investigation sequences when steady properties are present. The sequences can then be judged for stability using the Augmented Dickey-Fuller *(ADF)* test. If the time series is in a non-stationary state, differential operations must be performed on the original sequences until the state is stable as tested by *(ADF)*. The analysis

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involves checking if the test statistic is less than the critical value, indicating stability. A smaller critical value means a more stable sequence, and the *(p-value)* should be as close to 0 as possible to verify sequence stability. In the original redemption data sequence, the best *(p-value)* was just (0.002) for the electricity rate. We found to improve sequence stability for other indicators, hence we applied differential operation to the original time sequence. After the first-order difference and second-order difference operation for the subscription sequence, the best *(p-value)* is (0.0003) for *(Solar Rate),* (0.0001) for *(Petroleum),* and (0.001) for *(USD)* exchange rate, which is very close to 0. Therefore, except for *(Machinery and Electricity)* items, all the redemption data after the first-order difference operation are considered stable.

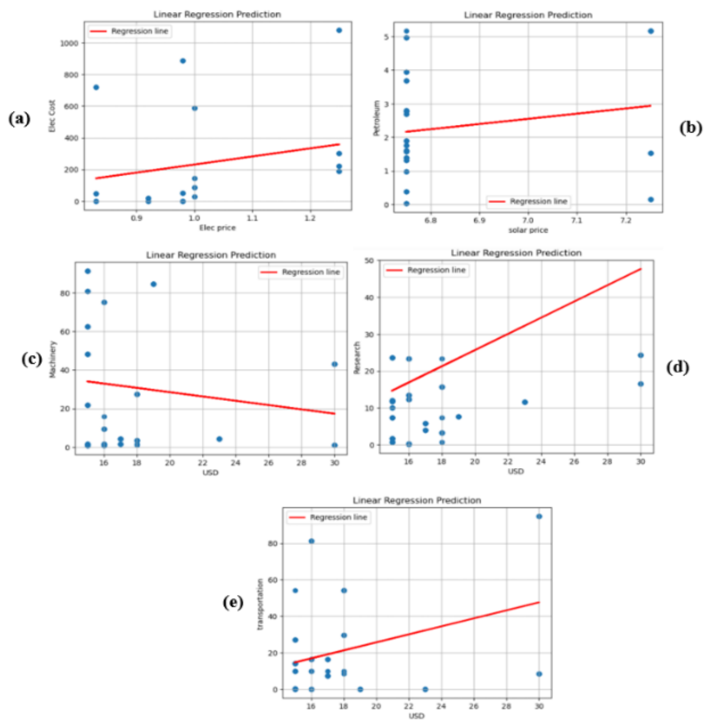

FIGURE 3 RESULTS OF REGRESSION ANALYSIS

Once the time series data has been processed to become stationary, a linear time series model can be created. To determine the autocorrelation and partial autocorrelation coefficients of the sequence, *(ACF and PACF)* diagrams are created. The *(ACF)* reflects the value of time series at time *(τ)* and the degree of linear dependence between time series at the time *(τ)*. On the other hand, the *(PACF)* measures the correlation between a variable and its lag. Disregarding any correlations at lower-order lags. The AR(p) model is established if the *(ACF)* diagram shows a truncated phenomenon. Conversely, the MA(q) model is established if the *(ACF)* diagram is truncated and the *(PACF)* coefficient displays a tail. If both the *(ACF and PACF)* diagrams exhibit a trailing phenomenon, it's important to verify whether the differential operation has transformed the time series into a stationary sequence.

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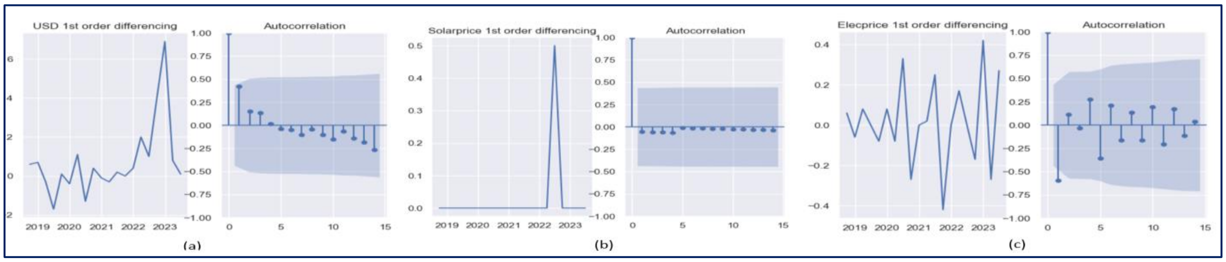

FIGURE 4 1ST.DIFF & ACF DIAGRAM (EXPENSES)

An *ARIMA* (p, d, q) model is established when the difference is stabilized, whereas an *ARMA* (p, q) model is established if not. To roughly determine the model order, Figures 4 and 5 display the first-order difference data's autocorrelation coefficient. The electricity items exhibit strong autocorrelations. However, the *(PACF)* method in *(Jupyter)* note can only calculate partial correlations for lags up to (50%) of the sample size, and the requested *(n_lags)* 14 must be < 10. Although the observed order may not always result in optimal modeling, optimization is necessary to determine the optimal model parameters during the actual modeling process.

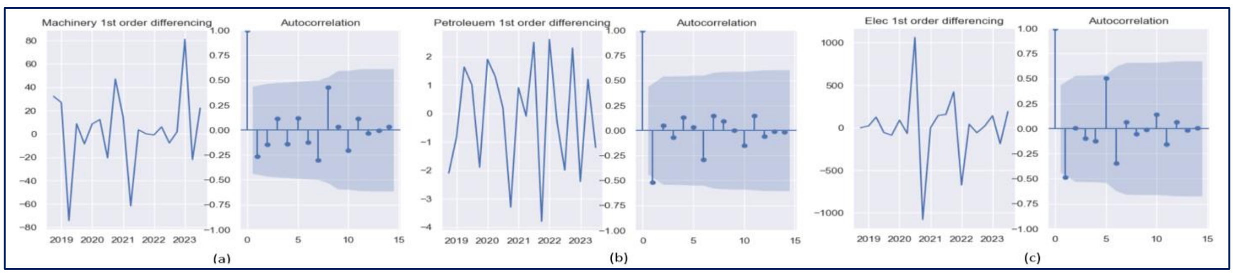

FIGURE 5 1ST.DIFF & ACF DIAGRAM (UNCERTAINTY INDICES)

Based on the *(ARIMA)* modeling process, we can optimize the parameters of our expenses and uncertainty indices data using the *(PMD_ARIMA)* method. To determine the *(ARIMA)* model's parameters, we employed the *(PMD_ARIMA)* optimizer in Python. The best-fit model for our expenses *(Machinery, Petroleum, and Electricity)* was [(2,2,1) (3,1,0) (2,1,1)], with total fit times of [0.04 sec, 0.02 sec, 0.05 sec]. To compare different models and determine which one is the best fit for the data, we used the *Akaike Information Criterion (AIC)* values to select the parameters with the lowest value, which were [196.83, 78.88, 292.97]. For our uncertainty indices *(USD, Solar, and Electricity),* we found the best-fit model to be [(0,2,0) (0,2,1) (3,1,0)], with total fit times of [0.00 sec, 0.05 sec, 0.04 sec]. Again, we used the *(AIC)* values to choose the parameters with the lowest values.

After determining how to fit the *(ARIMA)* model and its order, forecasting results for *(EDUA_ARIMA)* expenses and uncertainty indices were presented in Figures (6 and 7). The blue portion represents the original data set, the green portion represents the predicted data for the

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training set, and the orange portion represents the test data predictions. The evaluation process employs *(MAPE)* which is used to assess the regression error between the proposed model result and the ground truth, The mean squared error *(MSE)*, and root mean square error *(RMSE)* for regression evaluation indexes. However, the best Accuracy score for expenses is *Petroleum* by (61%), and uncertainty indices are (97%) for the *Solar Price Rate*, (84%) for the *Electricity Rate*, and (83%) for the *USD Exchange Rate*. The results indicate that expenditures on petroleum materials and the price of diesel are important in the study, in addition to that there is a strong relationship between them.

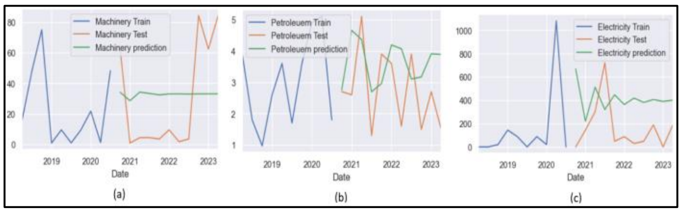

FIGURE 6 ARIMA_EXPENSES FORECAST RESULTS

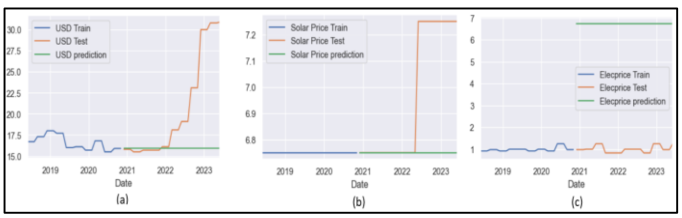

FIGURE 7 ARIMA_UNCERTAINTY INDICES FORCAST RESULTS

5.3 Results of EDUA_ LSTM

This paper depicts the *(LSTM)* model architecture in Figure (8). *(LSTM)* network has a specific structure consisting of (6) sets of features with a possible total of (12) input nodes. The first layer is the *(LSTM)* layer and has (12) hidden nodes. In this paper, the *EDUA_LSTM* has a timestep of (20), which utilizes the past (20) quarterly times information to predict the current quarter amount. At each timestep, the *(LSTM)* produces an output, but only the last output is selected as the input for the next dense layer. The dense layer comprises (8) nodes, and the last layer is the output layer which generates the forecast results for a selected data set.

Before creating the network topology, it's important to identify critical elements. We assume that the budget cycle is *(T)*. When making expenditure forecasts at time *(τ)*, it's necessary to consider the elements of the proposed model at time *(τ -T)*. First, you must select the interbank dollar rate. Any differences in the rate when purchasing budget items could impact sales and lead to penalties for failing to meet payment obligations. This could cause the agreed interest rate increase, as well as the annual interest rate return for users. Secondly, you need to determine the cost of energy, such as *(Electrical and Diesel)*, required for planned projects. Lastly, you'll need data on expenses for *(Machinery, Petroleum, And Electricity)* budget items.

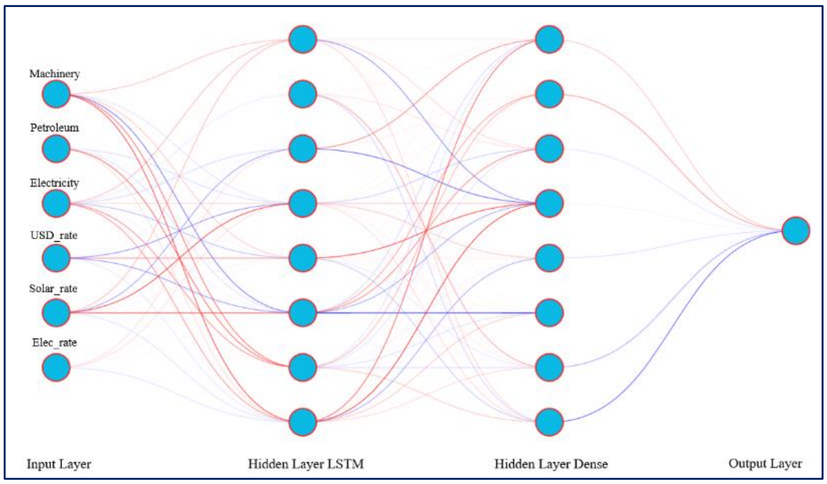

FIGURE 8 LSTM NETWORK

In this paper, the *(Timeseriesgenerator)* and the *(Minmaxscaler)* classes are used to generate input and output arrays for a time series forecasting model and fit them to the training data set to scale the data. In addition, the necessary *(Keras)* classes are imported, including *(Sequential, Dense, and LSTM).* The model is created as a *(Sequential)* object and an *(LSTM)* layer is added with (200) neurons. The *(LSTM)* layer output is then passed to a *(Dense)* layer with a single output neuron. After creating two new data frames and splitting them into training and testing sets, we set the *(nobs)* variable to (12), which means that the last (12) observations of the data frame will be used for testing, while the rest of the data will be used for training.

The parameters selected for the *(LSTM)* network in this study were as follows: an epoch was (50) which indicated (50) learning iterations during the training process. The learning rate was (0.05) which determines the step size when solving the gradient descent, and a small batch size of (1.0) which means that small batch gradient descent training is conducted for each data input. To measure the gap between predicted and real values and prevent overfitting or underfitting we employed the *Mean Squared Error* (MSE) loss function during training, to optimize original model parameters and reduce errors, we adopted the *(Adagrad)* optimization method. Additionally, we employed the *(ReLU)* function to increase the nonlinear expression ability of neural networks and address the vanishing gradient problem. We used the first (70%) of the data as the training set and the last (30%) as the testing set, along with the same experimental

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environment and error metric *(MAPE)* used for the *(ARIMA)* model experiments. Figures (9 and 10) display the results of the *(LSTM)* model, with the best model achieving *Accuracy* rates of (99.96%) for the *Solar* rate, (82%) for the *USD* rate, and (51%) for the *Petroleum* item.

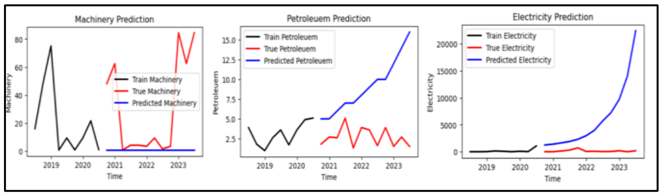

FIGURE 9 LSTM _ EXPENSES FORCAST RESULTS

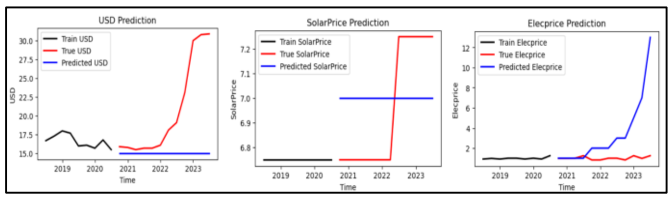

FIGURE 10 LSTM_UNCERTAINTY FORECAST RESULTS

5.4 Results of Distress Prediction Analysis

The objective of this research is to assess the financial performance of the *Nuclear Materials Authority*. The term *"Financial Performance"* refers to the organization's ability to meet its financial obligations. Hence, a deficit in budget items indicates a weak financial performance, whereas adequate disbursement limits demonstrate a strong financial performance. Nonetheless, financial performance has certain standards and benchmarks at an academic level to assess its position. Thus, the study employs artificial intelligence to analyze financial indicators, as has been seen in recent research, and assesses the performance of the tools used to analyze and predict the financial performance of the target case. A company's financial situation is vital for its sustainability, and early detection of financial crises is crucial for financial management. Financial ratio indicators are suitable for estimating model parameters, and a set of financial ratios is selected to create the initial feature set. Financial ratios are essential values used in FDP or similar studies. These ratios are calculated based on yearly financial statements such as income statements, profit and loss accounts, and balance sheets.

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Year	Rev-OB/MB	Rev-OB/FA	Rev-MB/FA	Exp-OB/MB	Exp-OB/FA	Exp-MB/FA	CUR	QR	CAR	DR	WOC	CENW
2019	0.06	0.32	0.26	0.05	1	0.96	0.88	0.85	0.003	0.002	-0.14	-5.40
2020	0.35	1.03	0.76	0.02	0.97	0.95	0.96	0.91	0.005	0.001	-0.04	-23.92
2021	0.06	0.32	0.26	0.05	1	0.96	1.1	1.0	0.005	0.001	0.088	6.77
2022	0.1	0.3	0.28	0.025	0.98	0.96	0.94	0.89	0.006	0.001	-0.05	-12.57
2023	0.06	0.32	0.26	0.05	1	0.96	0.97	0.91	0.003	0.001	-0.03	-27.27

The study first examines the most critical indicator that affects the financial performance of accounting units in the *Nuclear Materials Authority* across a five-year dataset as shown in Table 3. According to the descriptive analysis of financial ratios presented above

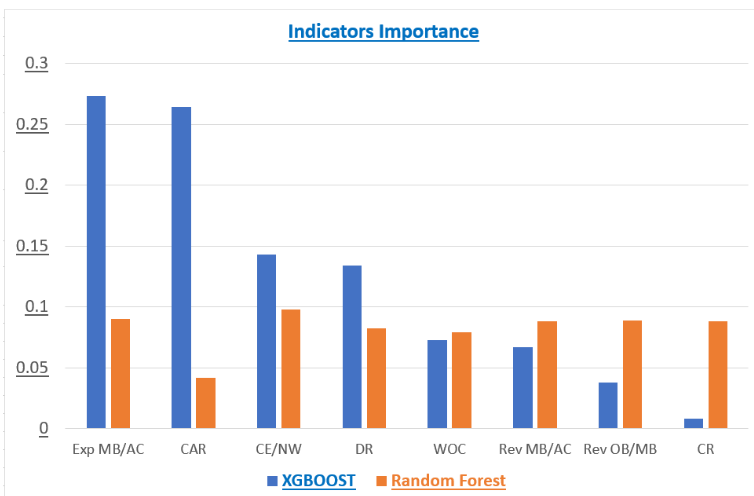

FIGURE 11 THE RESULTS OF PERFORMANCE INDICATORS PREDICTION

To assess the importance of the selected ratios, we employed both the *(Random Forest and XGBOOST)* techniques, as illustrated in Figure 7. The results showed that the *(XGBOOST)* model identifies the modified budget to actual expenses and cash ratio as the most critical indicators, while the *(Random Forest)* model assigns significant weight to the capital employed to net worth, modified budget to actual revenues, and original budget to modify the budget for revenues. It is worth noting that there is a strong correlation between the two models, particularly in terms of the capital indicators and the modification of the budget to actual revenues.

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TABLE 3 THE RESULTS OF MODELS PERFORMANCE EVALUATION

Model	Accuracy	Precision	Recall	F1 score
Random Forest	**0.69**	**0.72**	**0.78**	**0.75**
XGBOOST	**0.68**	**0.66**	**0.95**	**0.78**
K_nearest	**0.68**	**0.72**	**0.75**	**0.74**
Naïve Byas	**0.59**	**0.59**	**1.0**	**0.74**

Furthermore, we conducted experiments to compare model performance over five years preceding the status year. Table 7 presents *Accuracy*, *Precision*, *And Recall* results for each model. *Accuracy* scores for deep learning models varied across the five-year data set. Our assessment revealed that Random Forest achieved the highest accuracy at 69%, followed by XGBOOST and KNN at 68%, and the Naïve Byas model at the lowest accuracy score of 59%. Table 6 shows that the LightGBM model outperformed other models in terms of precision, recall, and F1 score.

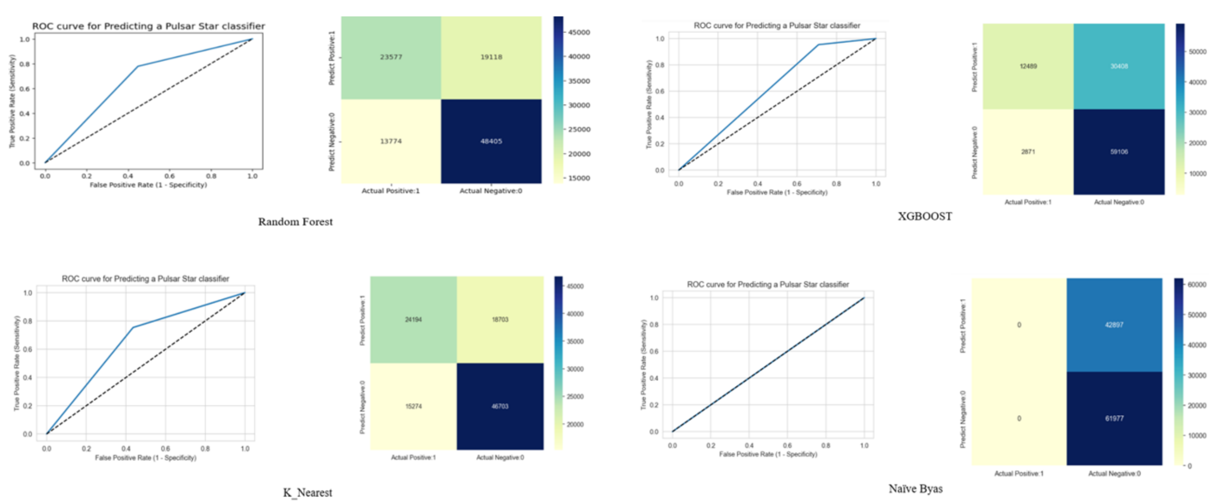

FIGURE 12 THE RESULTS OF ROC CURVE & CONFUSION MATRIX

Fig. 12 displays the ROC curves, PRC curve, and confusion matrix of the three ensemble methods. LightGBM demonstrated the best performance in terms of AUC, ACC, precision, and recall. Based on our analysis, we conclude that the LightGBM model is the most effective for the current case.

6. Conclusion

During the most recent phase of our investigation, we put up a proposition that would improve the procedure of budget planning and the monitoring of expenditures. By adding several different uncertainty indicators, such as currency rates and energy costs, our method, which we refer to as the EDU Approach, includes determining the components of the budget cycle that are subject to uncertainty. With this method, institutions are allowed to concentrate on their primary goals and accomplishments, and they are also allowed to diversify their financial and preparation strategies, both of which are very important for fostering sustainability. In the realm of public finance, we put up several suggestions that have the potential to be adopted to enhance the efficiency and effectiveness of financial management and to assist in the process of making better financial choices about scheduled expenditures and revenues. An application of a neural network model that is analogous to econometric models such as ARIMA was used to forecast the price of expenditures and uncertainty indices. For learning and training models, this required the use of past data. The petroleum rate had the highest accuracy score for costs, coming in at 61%. In terms of uncertainty indices, the solar rate had a score of 97%, the electricity rate had a score of 84%, and the USD rate had a score of 83%. After achieving accuracy rates of 99.96% for the solar rate, 82% for the USD rate, and 51% for the petroleum item, the LSTM model emerged as the most successful model. Although the Random Forest model assigned significant weight to the capital employment to net worth ratio, modified budget to actual revenues, and original budget to modify the budget for revenues, our findings indicated that the xgboost model identified in the modified budget to actual expenses and cash ratio as the most critical indicators. On the other hand, the Random Forest model assigned significant weight to the cash ratio. Our investigation revealed that there is a significant relationship between the two models, notably regarding the capital indicators and the adjustment of the budget to reflect real revenues. In addition to this, we carried out tests to evaluate the performance of the model throughout the five years that preceded the status year. The results of each model's accuracy, precision, and recall capabilities are shown in Table 7. As a result of our evaluation, we found that Random Forest earned the best accuracy, which was 69%. This was followed by XGBOOST and KNN, both of which reached 68% accuracy, while the Naïve Byas model received the lowest accuracy score, which was 59%. The results shown in Table 6 demonstrate that the LightGBM model performed better than other models in terms of accuracy, recall, and F1 score.

Our results, taken as a whole, indicate that the technique that we have provided has the potential to considerably enhance the process of budget planning and monitoring expenditures, as well as to assist institutions in making more informed financial choices about planned expenditures and revenues. However, we noticed that AI is a black box and there is a lack of explainability of some deep learning techniques that could result in a lack of trust, inequity, bias, and massive workforce replacement. For this reason, future research should consider explainable approaches such as case-based reasoning, and Shapley to make fiscal management able to interpret the distress results and increase the transparency and believability of 'black box' models.

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