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AN ENHANCED MODEL FOR PREMIUM MOTOR SPIRIT (PMS) PRICE PREDICTION AND MANAGEMENT IN NIGERIA USING MACHINE LEARNING

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ABSTRACT

Forecasting Premium Motor Spirit (PMS) prices accurately is crucial for economic stability and effective decision-making in Nigeria. Premium Motor Spirit (PMS), which is also known as petrol or fuel, plays a pivotal role in the country's economy, impacting transportation costs, inflation rates, and overall economic growth. However, the unpredictability of PMS prices prediction and management is influenced by factors like government policies, international oil markets, supply chain disruptions, stakeholders and interested cartels amongst others. This has created a constant price fluctuation, poor price control and management which eventually lead to fuel scarcity and high cost of fuel. The price control mechanism remains a contentious issue, with debates over its impact on the economy, government spending, and the welfare of ordinary Nigerians. This article presents an enhanced model for Premium Motor Spirit (PMS) price prediction and management in Nigeria using machine learning that will improve the price prediction and management system that will produce high degree of accuracy. The system was developed using visual studio C#, ML.Net model and Microsoft SQL server for its backend database. This model identifies key factors impacting PMS prices prediction and management that is used to forecast PMS prices over a specified time horizon such as daily, weekly, or monthly thereby enhancing economic planning and stability in Nigeria.

Keywords: Premium Motor Spirit, Machine Learning, Price Prediction, Management

INTRODUCTION

The Nigerian Premium Motor Spirit (PMS) market faces a distinct set of challenges, including subsidy frameworks, inefficiencies in the supply sequence, and geopolitical influences. These complexities demand a robust and adaptable forecasting approach. Traditional statistical models often fall short in capturing the non-linear and dynamic behavior of PMS prices in Nigeria. However, machine learning techniques, such as neural networks, support vector machines, and ensemble methods, offer enhanced flexibility and predictive accuracy. Recent research has validated the effectiveness of these methods in forecasting energy and commodity prices, underscoring their potential for PMS price prediction (Eze and Nwokoye, 2022).

According to Sun, Li and Sun, (2020) forecasting PMS prices is critical for policymakers and businesses, as PMS represents a key component of Nigeria's economy. It directly impacts transportation costs, inflation, and overall economic stability. Accurate price forecasts can help mitigate the adverse effects of price volatility and support strategic decision-making. Given Nigeria's heavy reliance on PMS and the recent global decline in oil prices, it is imperative to develop models capable of accurately predicting future pump prices. Effective forecasting of PMS prices in Nigeria is vital because of its profound economic implications, including effects on living costs and transportation. Price volatility, driven by indices such as global oil price fluctuations, exchange rates, supply chain interactions and frequent change of policy like fuel subsidy removal, poses significant challenges to economic stability (Nelson et al., 2018). Recent advancements in machine learning provide promising tools for improving the accuracy and reliability of price forecasting. By utilizing extensive datasets and enhanced machine learning algorithms which can uncover intricate trends and patterns in PMS price fluctuations, often surpassing the performance accuracy of traditional models (Adeniran and Alabi, 2023). According to Yusha'u and Nkiru (2024), incorporating machine learning techniques into PMS price forecasting aligns with the global shift towards data-driven decision-making in the energy sector. Around the world, countries are increasingly adopting machine learning and artificial intelligence to optimize energy management, predict market behavior, and strengthen economic resilience.

In Nigeria, the adoption of these technologies could greatly enhance the precision of PMS price forecasts, reducing economic uncertainties and enabling more effective policymaking. Additionally, advancements in computational capabilities and the availability of extensive data further underscore the practicality and advantages of this approach (Obi and Adeoye, 2023). Developing machine learning models for accurate price forecasting offers valuable visions for that that are involved in policy and decision making, business owners, and consumers, enable informed decision-making. This involves evaluating various advance machine learning models, identifying critical issues that affect prices, analyzing performance across regions, and comparing forecast accuracy with traditional methods (Shambulingappa, 2020).

Olayiwola and Seeletse, (2020) emphasized that accurately forecasting fuel prices is vital in ensuring the stability of economic and supporting effective decision-making in Nigeria. PMS is regarded as a foundation of the Nigerian economy, influencing transportation costs, inflation rates, and overall economic development. However, PMS price volatility is driven by indices such as government policies, global oil markets, and supply process disruptions, presents significant challenges for stakeholders.

Premium Motor Spirit (PMS) that is mostly referred to as petrol or gasoline, is a critical petroleum product primarily used as fuel for internal combustion engines in vehicles. It

serves as a cornerstone of the transportation sector and plays a pivotal role in the global economy. In Nigeria, PMS holds particular importance due to its significant influence on transportation costs and broader economic factors, including inflation and energy security (Smith, Tarui and Yamagata 2021). The global demand for PMS is determined by factors like economic growth, advancement in technological and evolving regulatory landscapes. Recent trends indicate a growing shift toward cleaner and more efficient fuels, driven by environmental concerns and the global push for sustainable energy solutions.

Nevertheless, PMS remains dominant, supported by well-established infrastructure and a slower transition to alternative energy sources in some developing countries of the world (Sultan, Alkhateeb and Fawaz, 2020). PMS is deeply intertwined with the development of the internal combustion engine and the automotive industry. Its origins can be traced back to the mid-19th century when Edwin Drake drilled the first successful oil well in Pennsylvania in 1859, marking the advent of the modern petroleum industry. Initially, refining processes prioritized kerosene production, with petrol considered a mere byproduct (Odido, Effiong and Eneje, 2023). In Nigeria, PMS holds critical importance due to its pervasive use and the government's fuel subsidy program aimed at ensuring affordability for the populace. However, these subsidies have been the topic of ongoing debate, with concerns over their economic sustainability and the burden they place on government finances (Adeniran and Alabi, 2023). In order to improve and reform the subsidy regime, the system has faced significant obstacles, including public opposition and political resistance.

The PMS supply chain in Nigeria is intricate, involving various stakeholders, from international suppliers to local distributors. Challenges such as fuel smuggling, inefficiencies in distribution, and regulatory bottlenecks contribute to price instability and frequent supply disruptions (Obi and Adeoye, 2023). Additionally, Nigeria's heavy dependence on imported PMS, due to inadequate local refining capacity, exacerbates these issues, leaving the market highly susceptible to fluctuations in global oil prices. Fluctuations in PMS prices have significant repercussions for the Nigerian economy. As emphasized by Eze and Nwokoye (2022) that persistence hike in fuel prices drive up transportation and production costs, fueling inflation and increasing the high cost of living. Conversely, lower fuel prices can diminish government revenue from taxes and subsidies, adversely affecting public expenditure and economic stability. These complexities are compounded by the energy sector's pivotal role as a major contributor to government revenue and foreign exchange earnings.

The future trajectory of PMS in Nigeria will likely depend on ongoing economic reforms, advancement in refining technologies and global energy trends Babalola and Salau (2020). Critical initiatives, including enhancing fuel efficiency, expanding various source energy and bolstering regulatory frameworks, are vital for fostering a stable and sustainable oil market. Moreover, leveraging advanced technologies like machine learning models for price forecasting and supply chain optimization offers promising opportunities to tackle persistent challenges in Nigeria's PMS market (Usman and Adebayo, 2023).

According to Bitirgen and Filik, (2020), the push towards expanding fuel production capacity and expanding difference source of energy, including investments in renewable energy, is expected to reduce the over dependence on fuel and its products that are on imported. The Nigerian government's strategic initiatives like the the Petroleum Industry Act, aim to attract investments, enhance transparency and increase effectiveness in the energy sector, which will play a key role in shaping the future of PMS in the country. Tayo and Adedayo (2022) stated that PMS price forecasting fosters cost-effectiveness and supports smart acquisition strategies to ensure survival in a volatile and competitive global market. In the study carried out by Al-Fattah, (2020), it addressed the issue of price volatility by proposing a novel artificial intelligence method. They found that the accuracy level can be enhanced through machine learning methods, particularly when the learning rate is set beyond a beyond threshold or set to its maximum value (Anazia & Okpako, 2022). This approach provided a valuable tool for predicting periods when regions or states are likely to face significant increases in PMS pump prices.

According to Abubakar, et al., (2024) they estimated that the ease to get of these petroleum products, based on all accessible reserves, will last more than 50 years with the application of machine learning-based approach. This highlights the essential roles played by crude oil in determining petrol prices. By analyzing PMS supply trends and identifying seasonality, they provided presented important ways that will improve effective planning and resource allocation. For example, rising petrol prices encourage vehicle owners to prepare financially ahead of time.. A deeper understanding of seasonality also aids in long-term strategic planning Anazia, Ojei and Okpor, (2024).

The recent hike globally in the price of crude oil is a noteworthy factor driving the price of petroleum beyond projection. The oil sector is divided into three main segments: the upstream segment, which focuses on exploration and production; the midstream segment, which handles the storage and transportation of natural gas and crude oil; and the downstream segment, which involves the refining, transportation marketing and storage of petroleum products like petrol and diesel (García and Martín, 2021). Each country's unique consumption and import patterns greatly influence PMS prices. For example, countries with lower import rates tend to experience lower prices for both diesel and petrol. Furthermore, oil marketing corporations have made adjustments to the additional taxes remitted to various state governments, which eventually help in determining fuel prices (Martin and Thompson, 2024).

In the work carried out by John et al., (2021), they highlighted the importance of predicting the price of petroleum products accurately and formulating effective policies to mitigate fuel-related economic shocks. Their study reviews various data mining techniques employed in petroleum price prediction, such as artificial neural networks, support vector machines and other intelligent optimization methods. These techniques are categorized into deep neural, regression models, networks, fuzzy logic systems and other hybrid models. The review provides a comprehensive discussion on the design of the various models and evaluates their accuracy in forecasting petroleum prices (Gupta and Nigam, 2020).

According to Agbo et al., (2022), it was noted that though numerous studies have applied machine learning techniques in the forecasting PMS and petroleum products in various countries which has presented several drawback has necessitated the design of this model. It underscores the need for the development of more accurate forecasting models, especially an enhanced learning models, tailored to the specific dynamics of the Nigerian market.

In the past, the existing models has failed to address the problems of PMS prices prediction and management which is characterized with frequent and unpredictable fluctuations in prices that creates economic instability and affect consumer's

purchasing power. This model improves the accuracy and relevance of PMS price forecasting in the country offering valuable insights for policymakers, businesses, researchers, indicating specific analysis, providing more detailed insights and identifying regional disparities in PMS pricing.

MATERIALS AND METHODS

The methodology adopted for this model is the Object-Oriented Methodology (OOM). This software development approach promotes and facilitates the reuse of software components. Using OOM, an information system can be built from reusable components, allowing for their efficient use in other systems. The methodology used for creating a Windows-based application to predict and manage Premium Motor Spirit (PMS) prices using machine learning follows a systematic process to ensure scientific precision and model accuracy. The development process includes the following steps

Step 1: Project Setup

The first step focuses on setting up the environment used for the development of machine learning and data analysis. This begins with creating a new Windows-based application in Visual Studio, a powerful integrated development environment (IDE) for .NET Framework applications. The chosen project type is "Windows-based App (.NET Framework)," selected for its capability to provide a user-friendly interface ideal for interactive analysis of data and model deployment. Once the project is initialized, key NuGet packages are installed to enable machine learning and data manipulation functionalities.

Step 2: Data Preparation

The second phase focuses on preparing the data for analysis, which is crucial for ensuring the accuracy and reliability of the machine learning model. The data, consisting of historical PMS price records, is stored in an Excel file within the project's Data folder. This organization guarantees that the data is structured and easily accessible for processing. The file should be organized with columns representing key features such as date and price to support precise analysis.

Step 3: Data Loading and Preprocessing

The final phase involves creating a dedicated class for data loading and preprocessing. This class utilizes the previously installed NuGet packages to perform several essential tasks:
Reading the Excel File: Using ExcelDataReader, the class reads data from the Excel file and converts it into a dataset compatible with machine learning algorithms.
Data Cleaning: The class cleans the data by addressing missing values, outliers, and inconsistencies, ensuring the dataset is of high quality and ready for model training.
Data Transformation: The data is transformed into a format suitable for machine learning models. This includes operations like feature extraction, normalization, and encoding, as needed, to prepare the data for effective model training.

Analysis of the System

The Enhanced Model for Premium Motor Spirit (PMS) Price Prediction and Management in Nigeria Using Machine Learning will foster economic stability and planning in the country by providing precise PMS price forecasts. The system is designed to develop an advanced model that integrates various machine learning algorithms, including deep learning methods like Long Short-Term Memory (LSTM) networks and ensemble techniques, to deliver highly accurate predictions tailored to different states in Nigeria. The methodology involves evaluating and comparing multiple models to produce the most effective forecasting approach, taking into account the intricate and non-linear components that traditional models may not capture.
By addressing these objectives, the system aims to provide more accurate, timely, and actionable predictions, ultimately supporting better decision-making for policymakers, businesses, and consumers, and contributing to improved economic stability and planning in Nigeria.

Architectural Design of the Proposed System

The diagram below in figure 1 shows the architecture of the model.

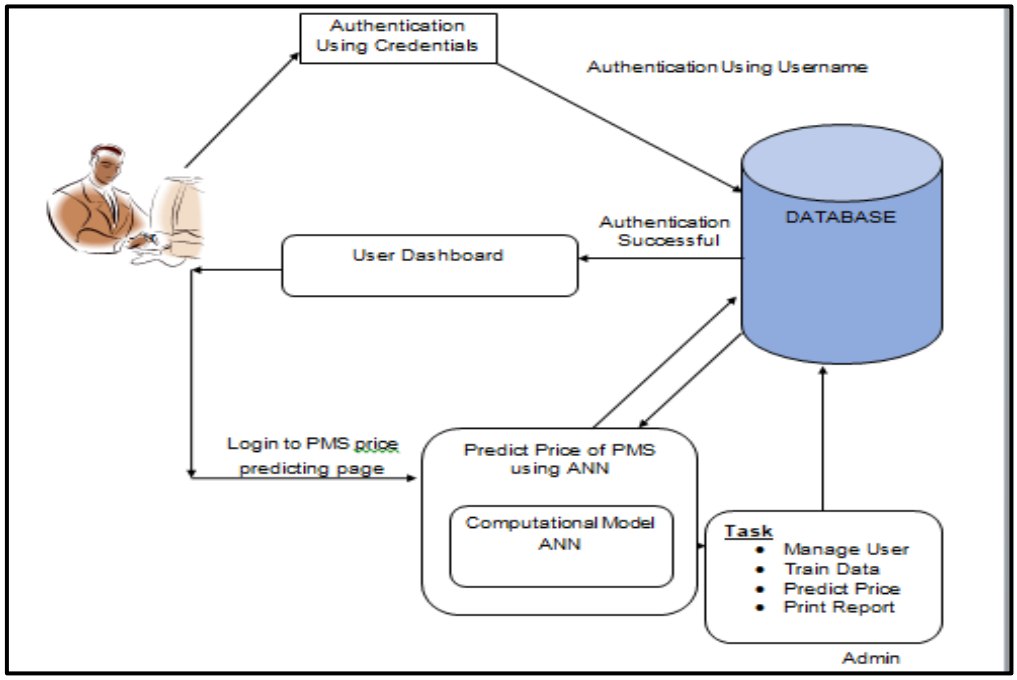

Figure 1: Architecture of the Model

Components of the Architecture

The architecture of the system, An Enhanced Model for Premium Motor Spirit (PMS) Price Prediction and Management in Nigeria Using Machine Learning involves several key components, each playing a critical role in the system's functionality.

Users: Users interact with the system to obtain PMS price forecasts across various time frames and regions. These stakeholders, including businesses and policymakers, rely on accurate and timely predictions to make informed decisions related to resource allocation, pricing strategies, and economic planning. Users also provide feedback on the system's performance, which is important for continuous improvement and system enhancement.

Administrator: Administrators oversee the system's operational aspects. They are responsible for training the data, ensuring that the machine learning models are updated with the latest and most relevant information. This includes managing the entire data pipeline, from data collection and preprocessing to integration into the forecasting model. Additionally, administrators handle user management, set permissions, and ensure secure access to the system's tools. They also generate reports summarizing forecast results and system performance, offering insights into forecast accuracy and regional price trends. These reports are fundamental for stakeholders to determine the effectiveness of the forecasts and make strategic decisions.

Computational ANN (Artificial Neural Network): The Computational ANN serves as the core forecasting engine of the system. It processes historical PMS price data to uncover complex patterns and relationships that traditional forecasting methods might miss. The ANN model is trained using this data, with hyperparameter tuning and network optimization to improve forecasting accuracy. Once trained, the model generates real-time forecasts considering the new input data. This component is essential for delivering accurate, dynamic predictions, which are used by users and reported by administrators.

Figure 2 below shows the E-R Diagram of Entire Model.

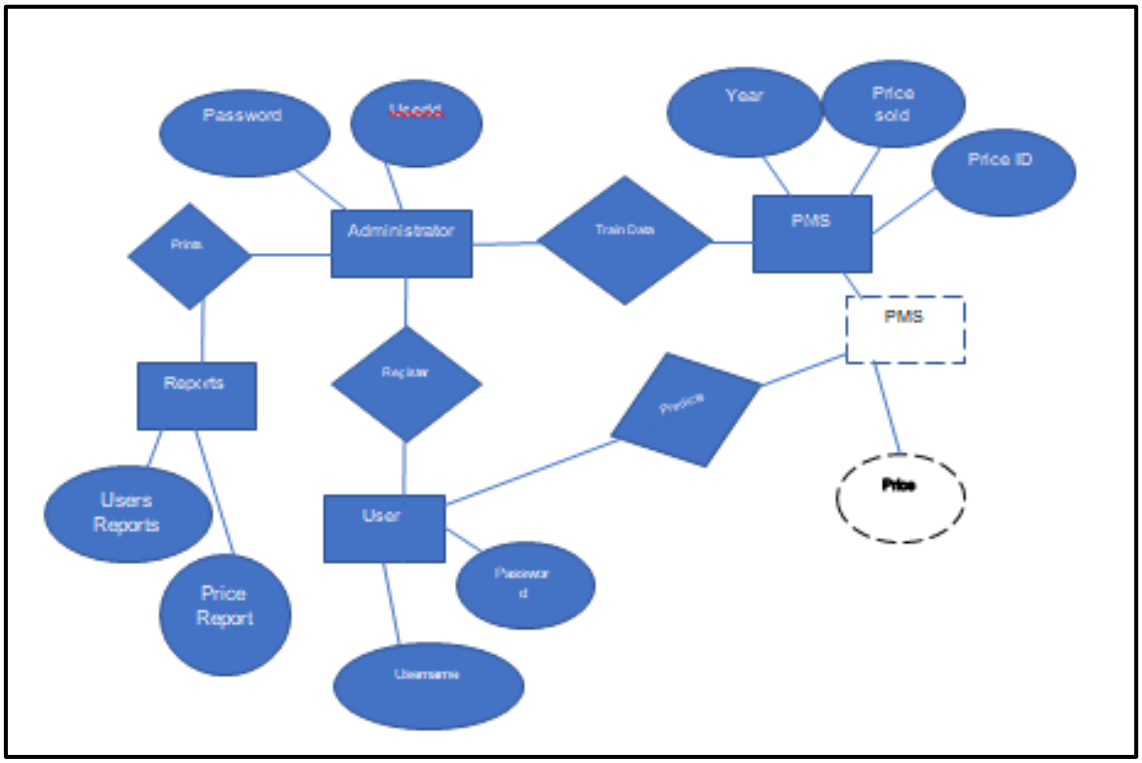

Figure 2: E-R Diagram of Entire Model

Activity Diagrams

Activity diagrams, the object-oriented counterpart of flowcharts and data flow diagrams from structured programming, show how a system's operations are carried out. The diagrams in figure 3 and 4 show the activity diagram and use case diagram of the model.

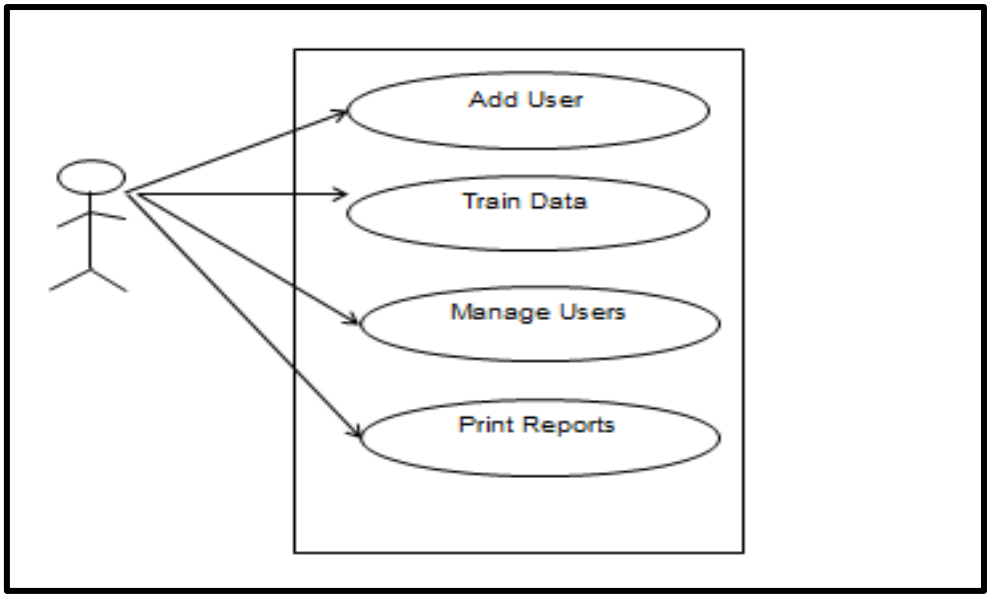

Figure 3: Activity Diagrams of the Model

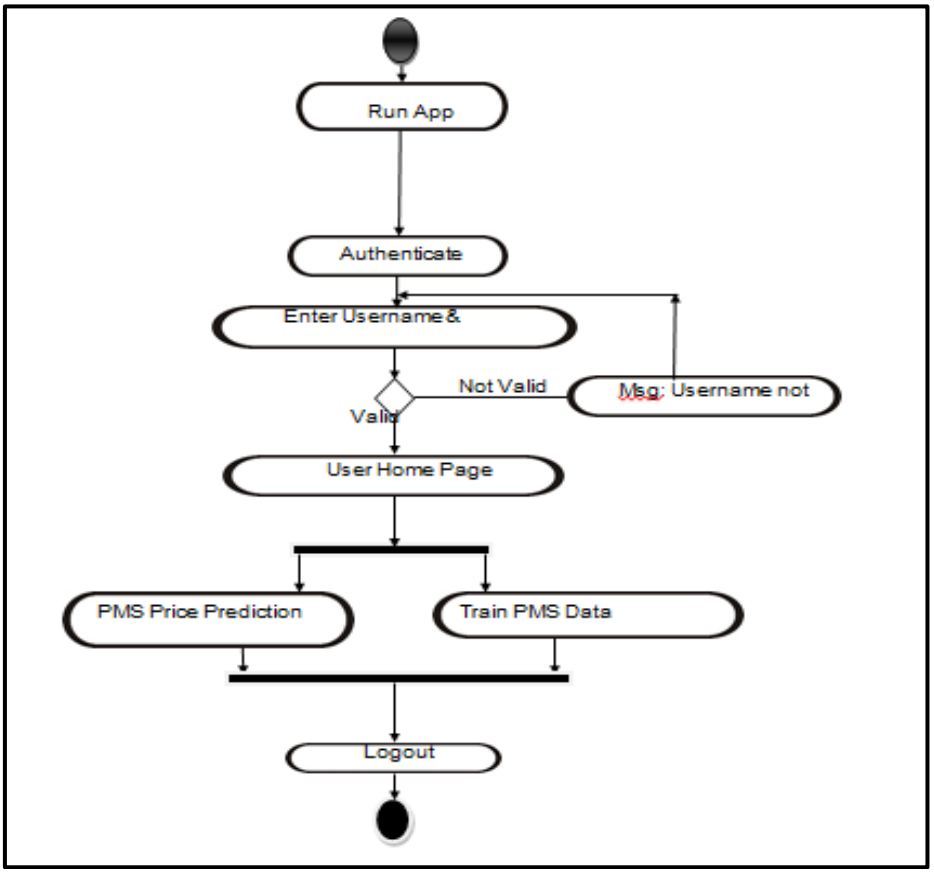

Figure 4: Use Case Diagram of the Model

Application Development

Development Phase

In this phase, the core functionalities of the application are developed and integrated. The process begins with setting up a Windows-based application in Visual Studio and installing the necessary NuGet packages, such as Microsoft.ML, Microsoft.ML.Data, Microsoft.Data.Analysis, ExcelDataReader, and ExcelDataReader.DataSet. These packages provide the essential tools for machine learning, data manipulation, and handling Excel files.

After the setup, a class is created to manage the loading and preprocessing of data. This class uses ExcelDataReader to read data from an Excel file, cleans it by addressing missing values and inconsistencies, and transforms it into a format that is compatible with machine learning algorithms. The data is then split into training and testing sets to support the model development and evaluation process.

The machine learning model is trained using the Microsoft.ML library. The model's architecture is chosen based on the nature of the data and the specific prediction

goals. Common regression algorithms, such as linear regression or decision trees, are used to predict PMS prices. The performance of the model is evaluated using metrics like Mean Absolute Error or Root Mean Squared Error to ensure that it is accurate and reliable.

Model Deployment

When the training of the model is completed and validated, it is integrated into the Windows-based application. The deployment process includes adding functionality to the user interface that allows users to input new data, trigger the prediction model, and display the results. Additionally, the application incorporates features for saving and loading models, empowering users to store and reuse trained models for future predictions. This comprehensive approach to system implementation guarantees that the Windows-based application effectively supports PMS price prediction through robust data processing, model training, and user interaction, ultimately delivering accurate and actionable insights.

Installation/Deployment Process

The installation and deployment process for the Windows-based application, designed to predict Premium Motor Spirit (PMS) prices, includes several key steps to certify the application is properly set up and functions correctly on end-user systems.

First, verify that the target system conforms with the software prerequisites. The application requires the .NET Framework, preferably version 4.8 or higher. If the framework is not already installed on the target machine, it should be manually installed from the Microsoft website or bundled within the application's installer. Additionally, some systems may need the Visual C++ Redistributable, so it's important to check for its presence and install it if necessary.

During the model's installation process, run the installer package on the target machine and follow the on-screen instructions. This typically includes agreeing to the license terms, selecting an installation directory, and confirming the installation options. After installation, it's imperative to authenticate that the application functions as expected by launching it and checking that all components are working properly. Confirm that all required dependencies are installed and configured correctly.

Finally, establish a support and maintenance plan. Provide users with documentation or training materials to help them understand how to use the application, input data, and interpret the results. Set up a technical support system to handle issues that may come up, and implement a regular update and patch schedule to maintain the application's functionality and address bugs. Create a feedback system to collect user input and report issues, which will help guide future updates and improvements.

RESULTS AND DISCUSSION

The Windows-based application model for Premium Motor Spirit (PMS) Price Prediction and Management in Nigeria Using Machine Learning represents a significant advancement over traditional, simplistic, and manual prediction methods. This evaluation compares the performance output of the new system with conventional approaches, focusing on parameters or metrics such as Mean Absolute Error, Mean Squared Error and R-squared to emphasize the system's accuracy, efficiency, and usability.

Accuracy and Precision

Traditional PMS price prediction methods often rely on basic methods like historical averages or linear extrapolation, which have limitations in predictive power. In contrast, the Windows-based application utilizes improved machine learning algorithms that deliver more accurate and precise forecasts. To assess accuracy, three key metrics are used:

Mean Absolute Error

Measures the average magnitude of errors in predictions by calculating the average of the absolute differences between predicted and actual values. A lower MAE indicates that the application's predictions are closer to the actual prices. Compared to traditional methods, the application demonstrates a significantly lower MAE, highlighting its improved accuracy.

Mean Squared Error

Calculates the average squared differences between predicted and actual values. This metric penalizes larger errors more heavily than MAE, making it useful for evaluating the effect of larger discrepancies. The application's MSE is substantially lower than that of conventional methods, showcasing its effectiveness in reducing prediction errors.

R-squared

Measures the proportion of variance in the dependent variable that can be explained by the independent variables (historical data). An R-squared value closer to 1 indicates that the model explains a large proportion of the variance. The Windows-based application attains an improved R-squared value compared to traditional methods, demonstrating a stronger alignment between the model's predictions and the actual data.

Efficiency and Scalability

Traditional PMS price prediction usually depend on manual calculations and are less adaptable to fluctuating market conditions. The new application automates the entire prediction process, significantly improving efficiency. Users can input data, process it, and generate forecasts much faster than with traditional methods. Additionally, the application scales efficiently with large datasets, allowing it to handle extensive historical data without performance loss—offering a clear advantage over manual or basic computational methods, which may struggle with large volumes of information.

Usability and User Experience

Traditional PMS prediction methods can be cumbersome and typically require substantial expertise to implement effectively. The Windows-based application, however, provides a user-friendly interface that simplifies complex processes, making it available even to users with minimal technical knowledge. Features such as interactive data input forms, intuitive displays of prediction results, and real-time feedback contribute to an enhanced user experience. Compared to traditional methods, which may involve complex spreadsheets or manual calculations, the application offers a more streamlined and user-friendly solution for users.

Flexibility and Adaptability

Traditional prediction methods often fail to adapt effectively to new data or changing market trends. In contrast, the Windows-based application incorporates a dynamic price module, enabling users to effortlessly update and integrate the latest pricing information. This flexibility ensures that predictions remain accurate and relevant, even as market conditions evolve. Additionally, the application's ability to retrain models with fresh data further enhances its

adaptability, distinguishing it from rigid, traditional approaches. The Windows-based application for PMS price prediction offers a clear advantage over traditional methods. By utilizing advanced machine learning algorithms, it achieves greater accuracy and precision. Its automated processes and user-friendly interface boost both efficiency and usability. Furthermore, the system's ability to handle extensive datasets and respond to new information highlights its versatility, making it an indispensable tool for modern PMS price forecasting.

Considering the performance metrics presented by this model which is based on the benefits of machine learning-based models, this application provides a more precise and reliable predictions and management of PMS prices system compared to other approaches used in Nigeria.

The diagrams in Figure 5, 6, 7 and 8 displays the prediction module, new price module, prediction result module and the training module of the Model respectively.

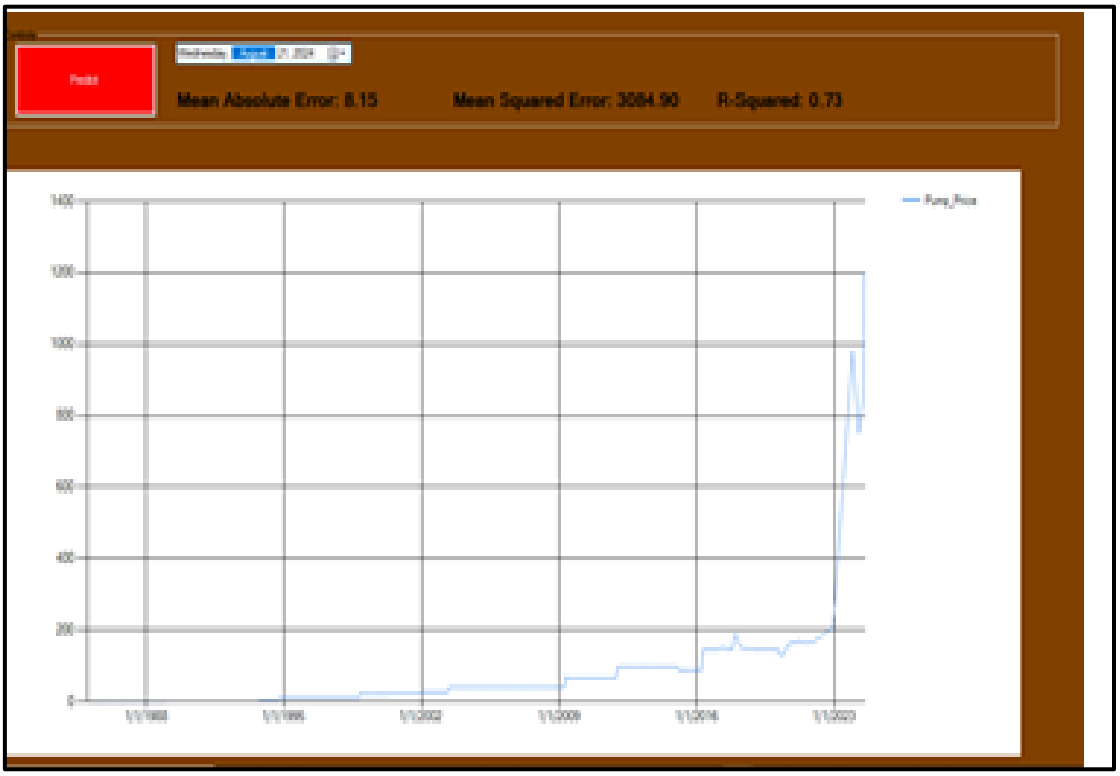

Figure 5: Prediction Module of the Model

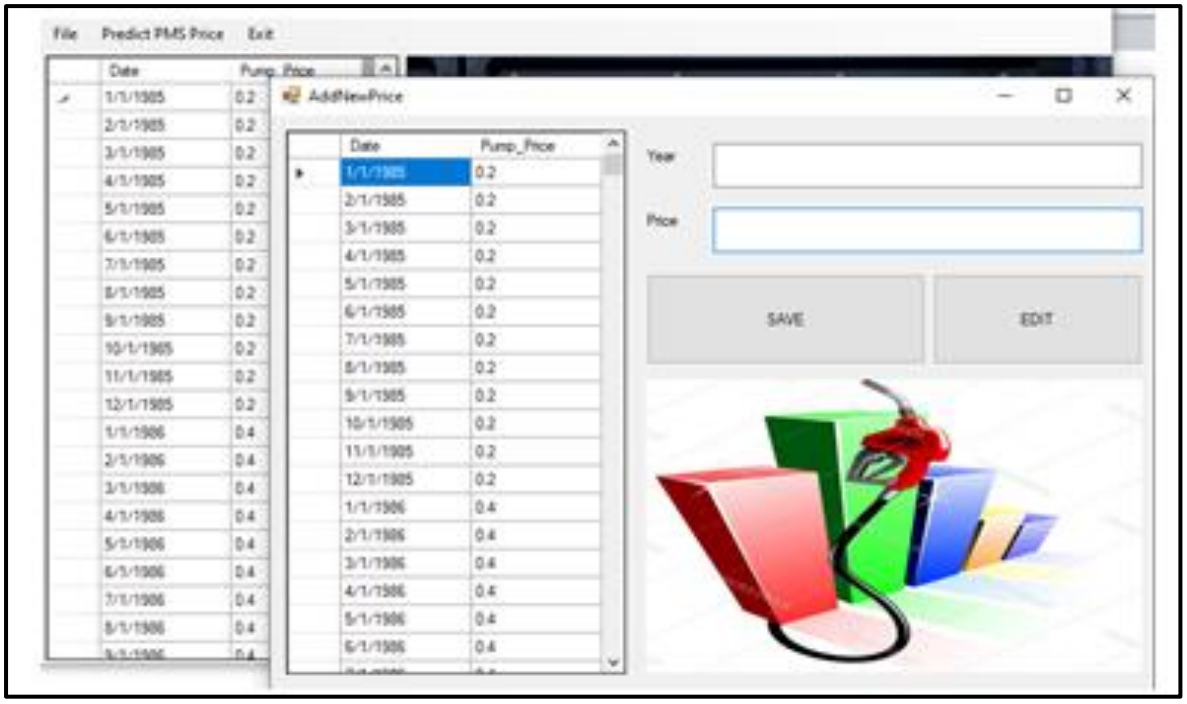

Figure 6: New Price Module of the Model

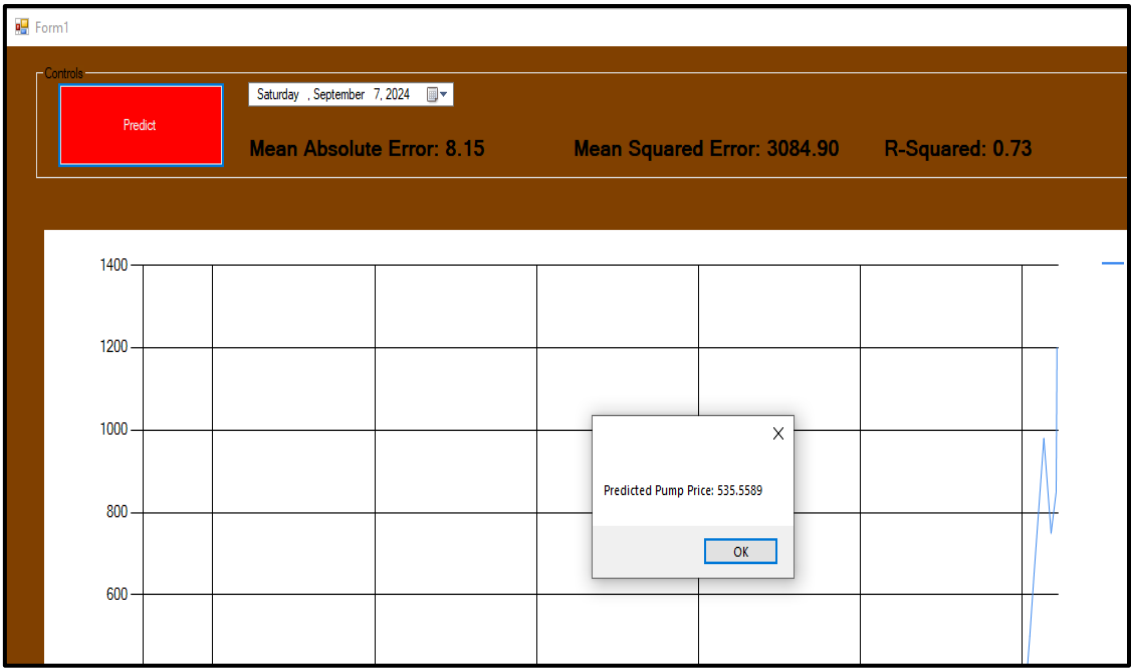

Figure 7: Prediction Result of the Model

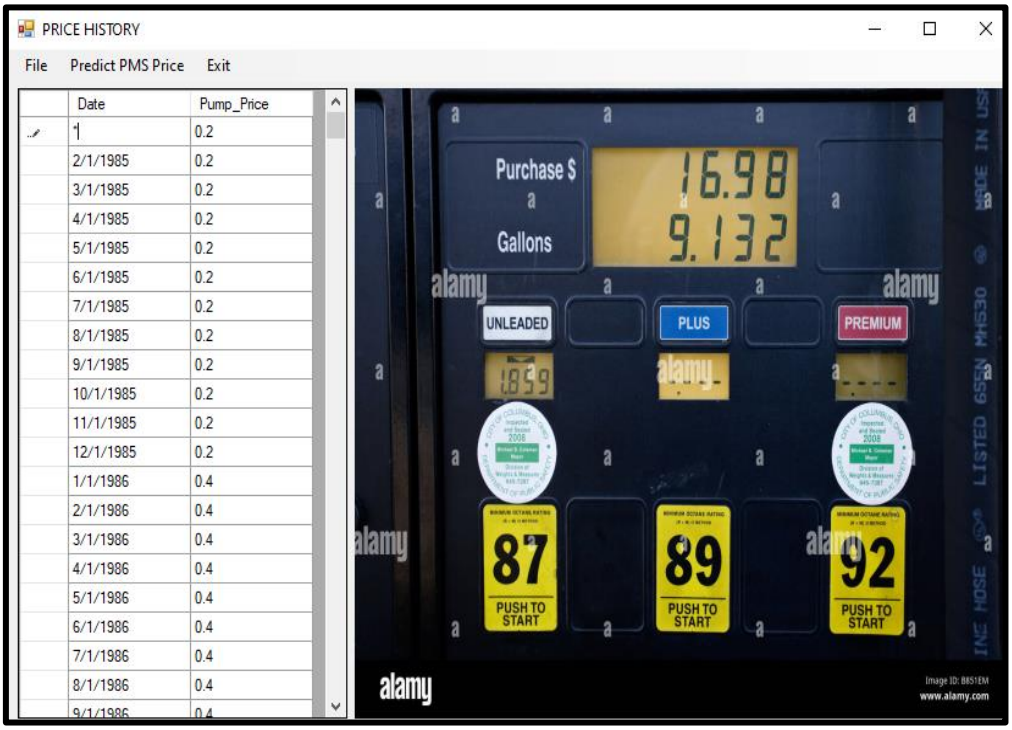

Figure 8: Training Module of the Model

CONCLUSION

The development and implementation of the Windows-based application for price predicting of PMS known as Premium Motor Spirit (PMS) Price Prediction and Management in Nigeria Using Machine Learning have brought significant improvements over traditional forecasting methods. The application harnesses advanced machine learning algorithms to achieve significant improvements in prediction accuracy. Key performance metrics like Mean Absolute Error and Mean Squared Error, are considerably lower than those of conventional methods, showcasing the application's enhanced precision in forecasting. Additionally, the higher R-squared value shows that the model captures a greater proportion of the variance in PMS prices, demonstrating a better fit with the actual data.

This model marks a significant leap forward in predictive analytics. Its integration of advanced machine learning techniques has resulted in improved accuracy, efficiency and user-experience as against the traditional methods. This model illustrates the capabilities of the machine learning-based models to transform forecasting practices and lays a strong foundation for future development. By incorporating additional factors, exploring new techniques, and expanding its scope, the application has the capabilities to evolve further, offering more accurate and actionable predictions in the petroleum industry and beyond.

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