A PROJECT REPORT ON

HYBRID APPROACH FOR CRUDE OIL PRICE PREDICTION USING PROPHET AND GRU

Submitted in partial fulfillment of the requirements for the award of the degree.

of

BACHELOR OF TECHNOLOGY

in

COMPUTER SCIENCE AND ENGINEERING

Under the guidance of

Mrs. ARCHANA.S, M.Tech., Ph.D.

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SREENIVASA INSTITUTE OF TECHNOLOGY AND MANAGEMENT STUDIES, CHITTOOR-517127, A.P.

(Autonomous)

(Approved by AICTE, New Delhi & Affiliated to JNTUA, Ananthapuramu)

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

(2024-2025)

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

CERTIFICATE

This is to certify that the project work entitled **"HYBRID APPROACH FOR CRUDE OIL PRICE PREDICTION USING PROPHET AND GRU"** is a genuine work of

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G RAMYA	**21751A0559**
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Submitted to the Department of Computer Science and Engineering, in partial fulfillment of the requirements for the award of the degree of BACHELOR OF TECHNOLOGY in COMPUTER SCIENCE AND ENGINEERING from Jawaharlal Nehru Technological University Ananthapur, Ananthapuramu.

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Submitted for University Examination (Viva-Voce) held on …………………………..

INTERNAL EXAMINER **EXTERNAL EXAMINER**

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Institute Mission

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M2: Ignite the students to acquire self-reliance in the latest technologies.

M3: Unleash and encourage the innate potential and creativity of students.

M4: Inculcate confidence to face and experience new challenges.

M5: Foster enterprising spirit among students.

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To contribute for the society through excellence in Computer Science and Engineering with a deep passion for wisdom, culture and values.

Department Mission

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- Inculcate confidence to face and experience new challenges from industry and society.
- Ignite the students to acquire self-reliance in the latest technologies.
- Foster Enterprising spirit among students.

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PROGRAMME EDUCATIONAL OBJECTIVES (PEO's):

PEO1: Excel in Computer Science and Engineering program through quality studies, enabling success in computing industry.**(Professional Competency)**.

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PEO3: Enhance knowledge by updating advanced technological concepts for facing the rapidly changing world and contribute to society through innovation and creativity **(Continuing Education and Contribution to Society)**.

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PSO2: Deploy the modern computer languages, environment, and platforms in creating innovative products and solutions.

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PO2 - Problem analysis: Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.

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PO4 - Conduct investigations of complex problems: Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.

PO5 - Modern tool usage: Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.

PO6 - The engineer and society: Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice.

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PO8 - Ethics: Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.

PO9 - Individual and team work: Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings.

PO10 - Communication: Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.

PO11 - Project management and finance: Demonstrate knowledge and understanding of the engineering and management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.

PO12 - Life-long learning: Recognize the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological changes.

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Course Out Comes for Project Work

On completion of project work the student will be able to

CO1. Demonstrate in-depth knowledge on the project topic.

CO2. Identify, analyze and formulate complex problem chosen for project work to attain substantiated conclusions.

CO3. Design solutions to the chosen project problem.

CO4. Undertake investigation of project problem to provide valid conclusions.

CO5. Use the appropriate techniques, resources and modern engineering tools necessary for project work.

CO6. Apply project results for sustainable development of the society.

CO7. Understand the impact of project results in the context of environmental sustainability.

CO8. Understand professional and ethical responsibilities while executing the project work.

CO9. Function effectively as individual and a member in the project team.

CO10. Develop communication skills, both oral and written for preparing and presenting project report.

CO11. Demonstrate knowledge and understanding of cost and time analysis required for carrying out the project.

CO12. Engage in lifelong learning to improve knowledge and competence in the chosen area of the project.

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CO – PO MAPPING

CO\PO	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PSO1	PSO2
CO.1	3	-	-	-	-	-	-	-	-	-	-	-	3	3
CO.2	-	3	-	-	-	-	-	-	-	-	-	-	3	3
CO.3	-	-	3	-	-	-	-	-	-	-	-	-	3	3
CO.4	-	-	-	3	-	-	-	-	-	-	-	-	3	3
CO.5	-	-	-	-	3	-	-	-	-	-	-	-	3	3
CO.6	-	-	-	-	-	3	-	-	-	-	-	-	3	3
CO.7	-	-	-	-	-	-	3	-	-	-	-	-	3	3
CO.8	-	-	-	-	-	-	-	3	-	-	-	-	3	3
CO.9	-	-	-	-	-	-	-	-	3	-	-	-	3	3
CO.10	-	-	-	-	-	-	-	-	-	3	-	-	3	3
CO.11	-	-	-	-	-	-	-	-	-	-	3	-	3	3
CO.12	-	-	-	-	-	-	-	-	-	-	-	3	3	3
CO	3	3	3	3	3	3	3	3	3	3	3	3	3	3

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Evaluation Rubrics for Project Work

Rubric (CO)	Excellent (wt = 3)	Good (wt = 2)	Fair (wt = 1)
Selection of Topic (CO1)	Selected a latest topic through complete knowledge of facts and Concepts	Selected a topic through partial knowledge off acts and concepts	Selected at opicthrough improper knowledge of facts and concepts
Analysis and Synthesis (CO2)	Thorough comprehensionthrough analysis/ synthesis	Reasonable comprehensionthrough analysis/ synthesis	Improper comprehensionthrough analysis/ synthesis
Problem Solving (CO3)	Thorough comprehension about what is proposed in the literature papers	Reasonable comprehension about what is proposed in the literature papers	Improper comprehension about what is proposed in the literature
Literature Survey (CO4)	Extensive literature surveywith standard References	Considerable literature survey with standard References	Incomplete literature survey with substandard References
Usage of Techniques &Tools (CO5)	Clearly identified and has complete knowledge of techniques & tools used in the project work	Identified and has sufficient knowledge of techniques & tools used in the project work	Identified and has inadequate knowledge of techniques & tools used in project work
Project work impact on Society (CO6)	Conclusion of project work has strong impact on society	Conclusion of project work has considerable impact on society	Conclusion of project work has feeble impact on society
Project work impact on Environment (CO7)	Conclusion of project work hasstrong impact on Environment	Conclusion of project work has considerable impact on environment	Conclusion of project work has feeble impact on environment
Ethical attitude (CO8)	Clearlyunderstands ethical and social practices.	Moderateunderstanding of ethical and social practices.	Insufficient understandingofethical and social practices.
Independent Learning (CO9)	Did literature survey and selected topic with little Guidance	Did literature survey and selected topic with considerable guidance	Selected a topic as suggested by the Supervisor
Oral Presentation (CO10)	Presentation in logical sequence with key points, clear conclusion and excellent language	Presentation with key points, conclusion and good language	Presentation with insufficient key points and improper Conclusion
Report Writing (CO10)	Status report with clear and logical sequence of chapters using excellent language	Status report with logical sequence of chapters using understandable language	Status report not properlyorganized
Time and Cost Analysis (CO11)	Comprehensivetime and cost analysis	Moderatetime and cost analysis	Reasonable time and cost analysis
Continuous learning (CO12)	Highly enthusiastic towards continuous Learning	Interested in continuous learning	Inadequate interest in continuous learning

ACKNOWLEDGEMENT

A Project of this magnitude would have not been possible without the guidance and coordination of many people. I am fortune in having top quality people to help, support and guide us in every step towards our goal.

Our team is very much grateful to the Chairman **Sri K. RANGANADHAM** Garu for his encouragement and stalwart support. We are also extremely indebted to the Secretary **Sri D.K. BADRI NARAYANA** Garu for his constant support.

We express our sincere thanks to our Academic Advisor **Dr. K.L. NARAYANA**, **M. Tech., Ph.D,** further, we would like to express our profound gratitude to our principal **Dr. N. VENKATACHALAPATHI, M.Tech., Ph.D.,** for providing all possible facilities throughout the completion of our project work.

We express our sincere thanks to our Dean (Academics), **Dr. M. SARAVANAN, M.E., Ph.D.,** further we express our sincere thanks to our Head of the Department **Dr. KARUNIA KRISHNAPRIYA.R, M.Tech., Ph.D.,** for his co-operation and valuable suggestions towards the completion of project work.

We express our sincere thanks to our guide **Mrs. ARCHANA.S, M.Tech., Ph.D̄.,** for offering us the opportunity to do this work under her guidance.

We express our sincere salutation to all other teaching and non-teaching staff of our department for their direct and indirect support given during our project work. Last but not the least, we dedicate this work to our parents and the Almighty who have been with us throughout and helped us to overcome the hard times.

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DECLARATION

We certify that

- The work contained in this report is original and has been done by me under the Guidance of my supervisor.
- The work has not been submitted to any other Institute for any degree or diploma.
- I have followed the guidelines provided by the Institute in preparing the report.
- I have conformed to the norms and guidelines given in the Ethical Code of Conduct of the Institute.
- Whenever I have used materials (data, theoretical analysis, figures, and text) from other sources, I have given due credit to them by citing them in the text of the report and giving their details in the references. Further, I have taken permission from the copyright owners of the sources, whenever necessary.

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ABSTARCT

Forecasting crude oil prices is essential for risk management and financial planning, but standard models fail to grasp both short-term fluctuations and long-term trends. This project proposes a hybrid method that merges Prophet for long-term prediction and GRU model for short-term prediction. To achieve higher precision, the Grey Wolf Optimizer (GWO) is used for hyperparameter optimization. Long Term trends are picked up by Prophet, while short-term fluctuations are handled by GRU. The hybrid framework combines both utilizing a weighted combination approach. Performance is measured in terms of MAE, RMSE, MAPE, R^2 Score. The Flask based graphical interface offers an interactive platform for real-time forecasting and visual illustration. Leveraging statistical techniques, deep learning, and metaheuristic optimization, the presented model outperforms conventional models. The system allows accurate forecasting, making it worthwhile for stakeholders in the energy industry. The combination of Prophet and optimized GRU guarantees a balanced prediction, enhancing the reliability of prediction. The hybrid model successfully solves the weaknesses of single forecasting approaches. Optimized performance through optimization methods renders the model strong and flexible. The ultimate system presents a scalable data-driven solution to crude oil price prediction.

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LIST OF ABBREVIATIONS

ARIMA	AutoRegressive Integrated Moving Average
GRU	Gated Recurrent Unit
GWO	Grey Wolf Optimizer
GPU	Graphical Processing Unit
IDE	Integrated Development Environment
LSTM	Long Short-Term Memory
MAPE	Mean Absolute Percentage Error
MSE	Mean Squared Error
RAM	Random Access Memory
R^2	Coefficient of Determination
RMSE	Root Mean Squared Error

CHAPTER 1

INTRODUCTION

Forecasting crude oil prices is a valuable contribution to international trade, energy economics, and financial markets, influencing investment policies and decision-making. Due to the volatile nature of crude oil prices, forecasting future trends is a difficult task to accomplish with certainty. Statistical and econometric forecasting models do not perform well in forecasting long-run trends and short-run fluctuations accurately. For this purpose, the present project suggests a hybrid method of forecasting using Prophet to forecast longrun trends and an GRU model to forecast short-run trends. The GRU model is further enhanced by utilizing the Grey Wolf Optimizer (GWO) as a hyperparameter tuner to make more accurate predictions. The proposed method makes use of Prophet to extract trends and seasonality and uses GRU's deep learning feature for short-run price movement prediction. The hybrid models combined using a weighted hybrid system provide higher forecasting accuracy than a single model. The project employs key performance metrics like Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and R2 in evaluating the efficiency of this method. An interactive graphical user interface (GUI) designed using flask further provides realtime visualization and comparison of forecast outputs. The hybrid forecasting model aims to outperform conventional models by employing statistical time-series forecasting, deep learning techniques, and metaheuristic optimization. The system provides an efficient and scalable solution to stakeholders in the energy sector, making crude oil price predictions more accurately for better financial and strategic decision-making.

1.1 OBJECTIVE OF PROJECT

This project aims to develop a robust crude oil price prediction model by integrating Prophet for long-term and an optimized GRU model for short-term prediction, supplemented by Grey Wolf Optimizer (GWO) for hyperparameter tuning. The goal is to attain the highest prediction accuracy by effectively capturing volatilities and trends. Performance metrics include MAE, RMSE, MAPE, and R2 Score, and interactive visualization is provided by a Flask based GUI. This hybrid model is efficient and scalable prediction instrument for financial markets, energy economics, and foreign trade.

1.2 PROBLEM STATEMENT

Because of market volatility, it is difficult to estimate the price of crude oil, and conventional models find it difficult to account for both short-term swings and long-term patterns. The accuracy of current statistical and machine learning methods is frequently lacking, necessitating efficient optimization. With the addition of Grey Wolf Optimizer (GWO) for hyperparameter tuning, this research suggests a hybrid model that combines Prophet for long-term trends and an optimized GRU for short-term forecasts. To enhance prediction accuracy, the system combines deep learning, statistical forecasting, and metaheuristic optimization. Crude oil forecasting is also made more feasible and dependable by the GUI, which allows for real-time display and model comparison.

1.3 LITERATUE SURVEY

Title: Reconstructing IMFs of Decomposition and Ensemble Model for Crude Oil Price Forecasting Using a Novel Approach

Year: 2024

Authors: O. Albalawi, J. Yu, M. Aamir, and M. Naeem.

This study combines ensemble machine learning with intrinsic mode function reconstruction to present a novel hybrid method for predicting crude oil prices. The process starts by breaking down the intricate crude oil price series into a number of IMFs using empirical mode decomposition. To remove noise and preserve important patterns, these elements are then selectively rebuilt. An ensemble model with a combination uses the enhanced IMFs as input characteristics.

Title: Predictive Crude Oil Price Modeling Using a Functional Data Analysis Framework with Mixed-Frequency Data and Derivative Information

Year: 2025.

Authors: Z. Tao, M. Wang, J. Liu, and W. Piao .

In order to enhance crude oil price forecasting, this study suggests a novel functional data analysis (FDA) paradigm that integrates mixed-frequency data and derivative information. In the framework of the FDA, the authors create an improved model that makes use of low-frequency fundamentals and high-frequency derivatives. This provides a more accurate depiction of intricate temporal linkages and volatility patterns. The approach presents a new way to handle time-series data that is distributed asynchronously.

Experiments demonstrate that the model performs better in predictions than both basic and state-of-the-art algorithms, making it a useful tool for economic market analysis.

Title: From Prediction to Gain: An Organized Analysis of Crypto currency Trading Models and Price Prediction Methods

Year: 2024.

Authors: J. Choi and O. Sultonov.

The present state of bitcoin trading models and forecasting methods is summed up in this thorough assessment, which also highlights the financial and predictive performance of these methods. It assesses the models' profitability and practicality by classifying them into deep learning, sentiment-based, and technical analysis models. In addition to rigorously examining risk-adjusted returns of prediction models and backtesting techniques, the authors draw attention to issues like market inefficiencies, information sparsity, and regulatory problems. This paper's methods and analysis can be used to prediction problems in highly volatile markets, such as energy commodities, albeit they are not limited to crude oil.

Title: An Innovative Hybrid Model for Crude Oil Futures Price Forecasting Based on Deep Learning and Error Correction

Year: 2023.

Authors: J. Wu, J. Dong, Z. Wang, Y. Hu, and W. Dou.

This study develops a hybrid model to increase the accuracy of crude oil futures price predictions by integrating deep learning with an error correcting procedure. The model uses an error correction model (ECM) to adjust for error deviations from equilibrium and LSTM for non-linear temporal patterns. Long-term equilibrium and short-term volatility are reconciled by the dual-structure model. The hybrid model's enhanced forecasting capacity over traditional models in terms of accuracy and dependability is demonstrated by experimental findings utilizing real futures data sets.

Title: An Examination of Machine Learning Models Applied to Forecasting the Prices of Petroleum Products

Year: 2024.

Authors: A. Y. Adam, O. B. Abodunrin, A. Abdulrauf, and P. O. Odion.

An overview of current developments in machine learning for estimating the price of petroleum products is given in this article. Random forests, support vector machines, artificial neural networks, and ensemble techniques are some of the algorithms used to categorize the literature. Data pretreatment techniques, performance indicators, and fundamental issues including overfitting, interpretability, and data quality are also defined in the article. The authors highlight the practical issues of using machine learning models in actual petroleum forecasting systems and offer ideas for future research in explainability and hybridization.

Title: A New Approach to Crude Oil Price Prediction Using ARIMA and LSTM Models Based on Stochastic and Deterministic Elements of LMD

Year: 2023

Authors: Z. ul Haq, S. S. Khan, M. Y. Amin, M. Naeem, J. Nasir, and M. Aamir.

The goal of this study is to remove deterministic and stochastic components from crude oil price time series using a hybrid modeling technique based on Local Mean Decomposition (LMD). Whereas LSTM models the stochastic residuals, ARIMA matches the deterministic trends. The model extracts the distinct individuality of signal components in order to improve the prediction. When tested on real data, the method outperforms separate ARIMA and LSTM models in terms of accuracy, demonstrating the effectiveness of component-wise forecasting.

Title: Using Hybrid Deep Learning to Forecast Gas Prices Using Temporal and Multi-Factor Features

Year: 2024

Authors: S. Zhang, H. Wu, J. Wang, and L. Du.

This study presents a hybrid deep learning framework for predicting gas prices that takes into account several external factors as well as temporal dynamics. The system combines LSTM layers for sequential learning with convolutional layers for pattern and sequence recognition. Predictions are made more precise by including external variables like weather, economic data, and inventories. Despite being centered on gas pricing, the technique improves temporal feature extraction and multi-source data fusion, which has implications for crude oil prediction.

Title: Forecasting Crude Oil Price Time Series Through a New and Innovative Approach Using Deep Learning, Time-Series Imaging, and Variational Mode Decomposition

Year: 2023.

Authors: Z. J. Peng, C. Zhang, and Y. X. Tian.

This paper proposes a novel approach to forecasting crude oil prices by combining deep learning, time-series imaging, and variational mode decomposition (VMD). The raw time-series data is broken down into useful sub-components by the VMD. Convolutional neural networks (CNNs) use them after being converted into visual representations. Temporal dynamics and delicate nonlinearities are preserved in this image-based approach. The suggested method outperforms conventional time-series models, demonstrating the value of combining visual deep learning and decomposition in financial forecasting.

Title: A Medium- to Long-Term Multi-Influencing Factor Copper Price Forecasting Model Using CNN-LSTM

Year: 2023.

Authors: L. Ding and M. Liu .

This work implies that a prediction model provided here can be expanded to energy commodities like crude oil, even though its use is limited to copper prices. In order to capture both temporal and spatial interactions between various elements, the model employs a hybrid CNN-LSTM model. Long-term dependencies are captured by LSTM, whereas local trends and characteristics are captured by CNN. This method works particularly well for medium- to long-term forecasting. The findings indicate that the same hybrid model can be used for other delicate commodity markets and are regarded as being very accurate and steady.

Title: Using a Decomposition Approach to Model and Predict Commodity Futures Prices Year: 2022.

Authors: L. Yu, S. Li, and A. Antwi

This article discusses a decomposition-based approach to commodities futures price forecasting that uses traditional machine learning methods in conjunction with empirical mode decomposition (EMD). By making it easier to distinguish between signal and noise, the decomposition improves the model's ability to represent different frequency components. Every element is predicted, and the predictions are aggregated. Tested on many commodities, including crude oil, the model's performance demonstrates improved accuracy and reduced prediction volatility.

Title: An Innovative Hybrid Method for Predicting Oil Prices Using Ensemble Thinking

Year: 2022.

Authors: J. Wang, W. Yang, P. Du, and Z. Li .

An ensemble-based hybrid crude oil price forecasting model is presented in this article. In order to capitalize on each base learner's unique abilities, it employs stacking and blending techniques. To separate the original time series into sub-series that are processed by specialized models, the method also uses decomposition. By reducing model bias and variance, the ensemble design improves accuracy and resilience. Its improved performance over single learners and simple hybrid models is confirmed by experimentation.

Title: An Ensemble Deep Learning Approach to Crude Oil Price Prediction

Year: 2017.

Authors: Y. Zhao, J. Li, and L. Yu.

An ensemble of deep learning models for predicting crude oil prices is presented in this paper. The authors use a combination of recurrent neural networks and deep belief networks to allow for both sequential linkages and hierarchical feature representations. . Despite being published before other advancements, this study established the foundation for later ensemble approaches and is still valuable due to its methodological contribution and consistency in performance across all crude oil benchmarks.

Title: Predicting Crude Oil Prices During Emergencies: Novel Data from Deep Learning and Machine Learning Models

Year: 2025.

Authors: W. Louhichi, Z. Ftiti, H. Ben Ameur, and H. Awijen

This study examines how well deep learning and machine learning models predict crude oil prices in times of crisis, like the COVID-19 epidemic and political unrest. The authors use models such as CNN, LSTM, and XGBoost. The findings show that while ML models remain competitive due to their interpretability and speed of training, deep learning models only slightly outperform them in identifying nonlinear trends and market shocks.

CHAPTER 2

SYSTEM ANALYSIS

2.1 EXISTING SYSTEM

The existing structure for crude oil price forecasting employs a hybrid approach consisting of Ensemble Empirical Mode Decomposition (EEMD), Autoregressive Integrated Moving Average (ARIMA), Support Vector Machine (SVM), and Long Short-Term Memory (LSTM). The model employs a decomposition-based ensemble technique, where information about crude oil prices is first decomposed into Intrinsic Mode Functions (IMFs) with the help of EEMD. These IMFs are subsequently separated into stochastic and deterministic components, and various models (ARIMA, SVM, LSTM) are applied on each. The final prediction is obtained by fusing the predictions of these components.

2.1.1. Disadvantages:

1. **Complexity of Decomposition-Based Approach:** The existing system comprises multiple decomposition, reconstruction, and forecasting steps, which is computationally intensive and hard to implement.
2. **Limited Feature Consideration :** The model primarily focuses on decomposing crude oil price data without considering external economic factors like exchange rates, supplydemand changes, and geopolitical events, which play a crucial role in oil prices.
3. **High Dependency on Decomposition Accuracy:** The forecast accuracy depends significantly on the reconstruction of the IMFs, which introduces uncertainty and potential errors.
4. **Limitations of ARIMA and SVM performance:** ARIMA is confronted by nonstationary data, and SVM may not always detect deeper temporal relationships as optimally as state-of-the-art deep learning methods.

2.2 PROPOSED SYSTEM

The suggested system proposes a hybrid forecasting system that unites Prophet for longterm trend prediction and GRU model for short-term price prediction, aided by the Grey Wolf Optimizer (GWO) for hyperparameter tuning. As opposed to the existing system relying on advanced decomposition techniques, the suggested model simplifies the forecasting process. Prophet accurately identifies seasonality and long-term trends, whereas GRU works better in modeling short-term changes. By tuning GRU's hyperparameters using GWO, the model ensures improved predictive accuracy. In addition, a GUI developed on Streamlit facilitates real-time forecasting, visualization, and model comparison, making the system more user-friendly and accessible. Performance is validated upon parameters such as MAE, RMSE, MAPE, and R2 Score accuracy and reliability. The proposed system upgrades the existing system by eliminating decomposition-based approaches, reducing computational time complexity, and providing better predictions reliability. Prophet and GRU can efficiently capture long-term as well as short-term trends. Moreover, the integration of an interactive GUI by using flask facilitates real-time analysis of data, a feature lacking in the present system. Improved error handling, a more dynamic forecasting framework, and improved usability, this system provides a more pragmatic and scalable solution to predicting crude oil prices.

2.2.1: Advantages:

1. **Enhanced Prediction Accuracy:** Combines Prophet for long-term and GRU model for short-term prediction, with GWO for hyperparameter tuning.
2. **Lower Computational Complexity:** Avoids the use of decomposition methods such as EEMD, reducing implementation complexity without compromising accuracy.
3. **Enhanced Non-Stationary Data Management**: Prophet manages seasonality, while GRU manages short-term fluctuations for an equilibrium prediction.
4. **Hyperparameters Fine-Tuned:** GWO optimizes GRU parameters to minimize overfitting and underfitting risks.
5. **Scalability & Flexibility:** Scalable to forecast other energy commodities such as natural gas and electricity prices.

2.3 FEASABILITY STUDY

2.3.1 Technical Feasibility

Technical feasibility of the proposed hybrid crude oil price forecasting system is well established by the availability of robust and advanced forecasting architectures. The project utilizes Prophet, a robust open-source time series forecasting model by Facebook, which is effective for long-term trend captures. In addition, the GRU-based deep learning model is implemented with TensorFlow/Keras, which is versatile and has robust tools for training and testing. For hyperparameter tuning, the Grey Wolf Optimizer (GWO), a metaheuristic algorithm, is computationally efficient and easy to implement. The whole model training and deployment can be accomplished on standard GPU-supported machines, and hence technical requirements are within reach.

2.3.2 Operational Feasibility:

The feasibility of operation of this project is high because of its ease of use and automated pipeline. After the training process is over, the model can be utilized by non-technical users through the GUI. The use of Streamlit GUI makes the users able to enter new data and produce forecasts in real time, making the system feasible for business analysts and stakeholders from the energy and financial domains. The hybrid model needs very little user intervention after deployment, and the modular architecture facilitates easy updates and retraining when new data are available. The system is feasible for operational deployment in real-world applications like monitoring the oil market, financial planning, and risk management, adding to its usability and applicability across domains.

2.3.3 Economic Viability

The economic feasibility of the hybrid forecast system is strong with the use of entirely open-source software such as Prophet, TensorFlow, and Python libraries. The GWO algorithm and all the supporting frameworks are license-free, which leads to a significant decrease in development costs. Hardware needs are minimal; training and inference can be efficiently carried out on a reasonably powered GPU-based setup. The economic benefit of accurate crude oil forecasting comprises better financial planning, better inventory management, and reduced economic risks to oil price-dependent industries.

CHAPTER 3

SYSTEM DEVELOPMENT MODEL

For the development of the crude oil price prediction system using a hybrid forecasting model, the Iterative Development Model has been selected as the most appropriate methodology. This model aligns well with the experimental and dynamic nature of datadriven forecasting systems, where models are refined progressively through evaluation, feedback, and retraining. The Iterative Development Model supports continuous improvement by developing the system in multiple cycles, allowing better feature integration, performance enhancements, and real-time feedback incorporation. Each iteration results in a functional module that can be tested and evaluated.

Requirement Analysis

During this phase, the system's functional and technical requirements are identified. This includes defining the objectives of forecasting crude oil prices accurately for strategic planning and risk management. Requirements for data collection, preprocessing, and handling missing values are clarified. The expected input variables (e.g., price, volume, high, low, etc.), forecasting horizon, and evaluation metrics (RMSE, MAE, MAPE, R^2) are also established. Consideration is given to computational constraints and the tools to be used, such as Prophet for trend prediction, GRU for residual learning, and GWO for optimization. Requirements are refined throughout development as insights are gathered from testing and feedback.

System Design

Based on the gathered requirements, the architecture of the hybrid prediction system is designed. The modular framework includes components for data preprocessing, Prophet modeling for long-term trends, GRU modeling for short-term residuals, and GWO for GRU hyperparameter tuning. The integration strategy for combining the outputs of Prophet and GRU using a weighted sum is also decided in this phase. Additionally, the interface design is considered using Streamlit, allowing users to interact with the system and view forecasts visually. Design considerations also include data smoothing techniques and the modular flow for hybrid integration and evaluation.

Implementation and Training

The implementation begins with the Prophet model for trend prediction followed by extraction of residuals. The residuals are then smoothed using methods such as Savitzky-Golay filtering before training the GRU. The GRU model is optimized using Grey Wolf Optimizer to identify the best hyperparameters for enhanced performance. The models are trained with appropriate loss functions and tuned to prevent overfitting using regularization techniques such as dropout, early stopping, and learning rate scheduling. The hybrid output is computed as a weighted sum of Prophet prediction and GRU-predicted residuals, with the weight parameter optimized to minimize forecasting error.

Testing and Evaluation

The developed hybrid model is evaluated on a separate test dataset using metrics like RMSE, MAE, MAPE, and R^2. The performance of individual models (Prophet and GRU) and the combined hybrid model is analyzed and compared. Plots for predicted vs. actual values, residuals, and error distributions are generated to visualize model accuracy. Unit testing is performed for each module, including data preprocessing, model training, and hybrid integration. Observed shortcomings, such as underfitting, overfitting, or low residual accuracy, are documented and used for further tuning.

Feedback and Refining

Feedback from evaluation results and visual inspection is used to refine the model. This includes modifying GRU architecture, updating GWO search parameters, improving data preprocessing steps, and adjusting the hybrid combination weight. Additional data cleaning or feature engineering may be introduced in the next cycle. GUI enhancements are also implemented based on usability feedback. This iterative improvement continues until the system meets the desired forecasting performance and user experience goals. The final iteration results in a fully functional, deployable crude oil prediction system with an interactive GUI for real-time forecasting.

CHAPTER 4

SYSTEM DESCRIPTION

4.1.PROBLEM DEFINITION

Crude oil prices are extremely volatile and driven by many dynamic factors, so it is difficult to predict them accurately. Non-linear trends cannot be modeled with conventional statistical models, and single deep learning models lack long-term trends. This project attempts to address this issue by developing a hybrid model consisting of Prophet for long-term trend prediction and a GRU model optimized with Grey Wolf Optimizer for short-term residual prediction. The final model integrates both the outputs with a weighted approach and is deployed via a Streamlit-based GUI for real-time forecasting of crude oil prices.

4.2. OVERVIEW OF THE SYSTEM

The system suggested is a hybrid crude oil price forecasting system that utilizes both statistical and deep learning approaches to enhance predictive performance. It employs Prophet for long-term trend modeling and a Grey Wolf Optimizer (GWO)-tuned GRU model for short-term residuals modeling. The hybrid scheme improves performance by using both models with a weighted scheme. The system also includes a GUI implemented with Streamlit for an interactive real-time forecasting and visualization system. The system has the following modules:

- Input Module: Accepts historical crude oil price data, with columns such as Date, Open, High, Low, Close, Volume.
- Data Preprocessing Unit: Deals with missing values, date format conversion, data scaling/normalization, and sequence preparation for modeling.
- Prophet Forecasting Engine: Generates long-term trend forecasts using Facebook's Prophet model.
- Residual Modeling Module: This computes residuals of the Prophet model and feeds these into the GWO-tuned GRU in order to learn short-term updates.
- Hybrid Integration Unit: Combines the outputs of Prophet and GRU with a weighted sum under the control of an optimized alpha parameter.

- Unit for Output Assessment: Computes metrics like MAE, RMSE, MAPE, and R^2 to assess model performance.
- GUI Interface: Implemented with Flask GUI in an effort to allow users to see predictions, input parameters, and interactively forecast future crude oil prices.

4.3 SYSTEM ARCHITECTURE DIAGRAM

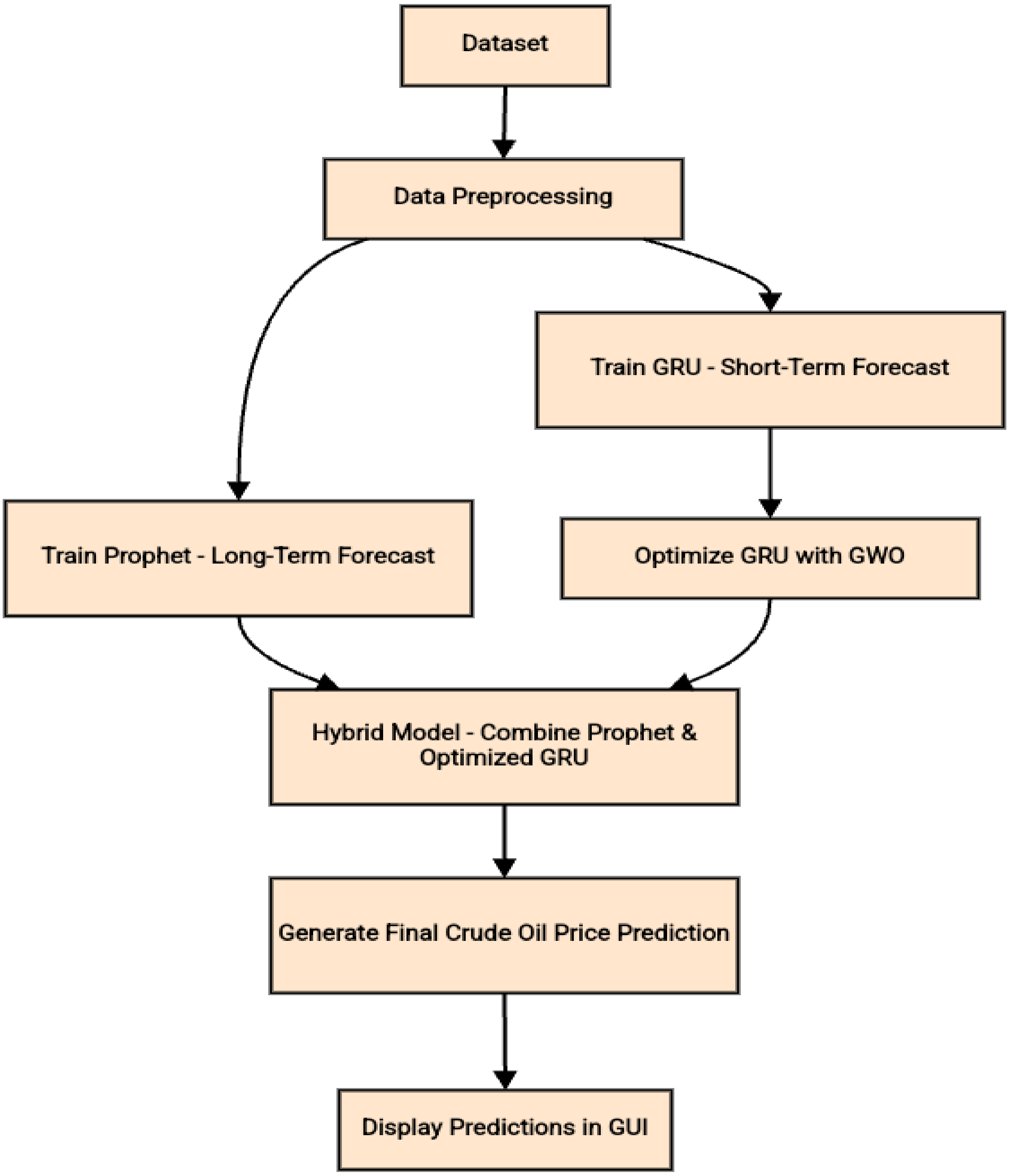

Fig 4.3.1: System Architecture Diagram

CHAPTER 5

SYSTEM DESIGN

5.1 MODULE DESCRIPTION

5.1.1 Data Preprocessing

The foundation of the entire forecasting pipeline is the Data Preprocessing Module. Missing numbers, undesired formatting, and non-numeric values are among the irregularities that must be addressed before model training on real-world time-series data, which typically includes data on crude oil prices. In order to perform temporal indexing, this module first imports the crude oil.csv dataset and date-parses the Date column into Python datetime format. It ensures that all extra characters (such dollar signs, commas, or spaces) are removed and that columns like Open, High, Low, Close/Last, and Volume retain numerical integrity. Depending on how they affect the distribution of the data, outliers and null values—if any—are either treated or left out.It ensures that all extra characters (such dollar signs, commas, or spaces) are removed and that columns like Open, High, Low, Close/Last, and Volume retain numerical integrity. Depending on how they affect the distribution of the data, outliers and null values—if any—are either treated or left out. In order to maintain temporal order—which is crucial when it comes to time-series modeling—it also sorts by date. To replicate real forecasting situations, the cleaned data is divided into training and test sets. The modeling modules then receive these cleaned subsets. In the absence of this module, downstream models would produce predictions that are unreliable and have poor data quality.

5.1.2 Exploratory Data Analysis(EDA)

This module uses statistical and graphical ways to prize precious perceptivity from the dataset. Before developing prophecy models, it's critical to comprehend the long-term trends in crude oil painting oil prices. Time- series plots are used to graph the data at this stage so that long- term patterns, short- term oscillations, and any seasonality or periodic trends can be seen. Plots analogous as moving pars are used to count noise and highlight underpinning trends. Rolling standard diversions or quotidian price change histograms are used to measure volatility. Trend- cycle plots or corruption plots are used to examine seasonality. also, the EDA module identifies pricing behavior changepoints or abnormalities that call for spare attention.Additionally, the EDA module identifies pricing behavior changepoints or abnormalities that call for spare attention. The findings guide model complexity and data smoothing ways like moving pars, as well as tuning parameters for the Prophet model(analogous seasonality modes or changepoint former scale).

5.1.3 Trend Modeling (Prophet)

This module uses the Facebook Prophet algorithm to capture the long- term trend and seasonal patterns of crude oil painting oil prices. Prophet is an accretive model designed especially for auguring time series with multitudinous trend changepoints and high seasonality. The gutted training data, reorganized into Prophet's ds(date) and y(value) formats, serves as the module's input. Three main factors are also described by Prophet fitting a model trend, seasonality, and leaves(where applicable). Crude oil painting oil prices are particularly susceptible to periodic seasonality and unlooked-for shifts(due to profitable or geopolitical shocks, for illustration).

5.1.4 Residual Modeling (GRU)

The short- term irregular patterns and noisy conduct in the residual series generated by the Prophet model are the focus of the GRU Residual Learning Module. Compared to LSTMs, GRUs(restarted intermittent Units), a subset of intermittent neural networks(RNNs), bear lower parameters to recall long- term dependences, making them especially suitable for successive input. In order to homogenize the data, residuals are first gauged in this module using a MinMaxScaler or StandardScaler. The residual time series are also converted into sequences suitable for supervised knowledge using a sliding window approach. These sequences are used to train and initialize the GRU model in order to comprehend the residuals' temporal structure.These sequences are used to train and initialize the GRU model in order to comprehend the residuals' temporal structure. The result is the GRU- predicted residual element for the test and train sets. After learning the short- term diversions, the GRU model incorporates them into Prophet's long- term prognostications to produce a superior crossbred model with advanced delicacy.

5.1.5 GWO Optimization Module

The Grey Wolf Optimizer(GWO), a metaheuristic algorithm predicated on the social structure and stalking medium of slate wolves as inspired by nature, is used in this module to optimize the GRU model's performance. Model performance is significantly impacted by hyperparameters analogous as the number of GRU units, learning rate, batch size, and number of training periods. The GWO module fully looks for the hyperparameter configuration that maximizes prophecy error(analogous as RMSE) on a evidence set because manual tuning is constantly ineffective and wrong. An original population of" wolves"(candidate results) is generated, their positions are streamlined using the GWO update rules, and they are calculated using a fitness function(evidence RMSE). The GRU model is retrained using the optimized hyperparameters once the ideal setup has been determined. The GWO module significantly improves the GRU's capacity to represent residuals directly and makes the crossbred model function well in a variety of scripts.

5.1.6 Hybrid Forecasting

The Prophet model, which detectsmacro- position patterns, and the GRU model, which detects delicatemicro- position oscillations, are the two soothsaying ways that are combined in the Hybrid Prediction Module. The module generates the final crude oil painting oil price read by calculating a weighted sum of the Prophet trend and GRU-predicted residuals. The following formula is applied Cross-validation is used to OK-tune this parameter and determine the value that minimizes RMSE. Prophet's rigidity to erratic time intervals and changepoints is profitable to the crossbred model, while GRU increases delicacy by correcting for flash prophecy crimes. This module's affair is the final prophecy , which is used for projecting future dates as well as testing nonfictional data.

5.1.7 Model Evaluation

The Prophet, GRU, and crossbred models' auguring capacities are objectively assessed in the Evaluation Module. On the test set and future cast horizon, it calculates significant error measures analogous as R- squared(R^2), Mean Absolute Error(MAE), Mean Absolute Chance Error(MAPE), and Root Mean Squared Error(RMSE). These criteria make it possible to compare the performance of the models and determine whether the crossbred model outperforms its element rudiments. In addition to numerical evaluation, the module generates graphical plots for the model's interpretability, analogous as performance graphs, residual plots, and factual vs. predicted line maps.The evaluation module verifies that the prognostications are visually harmonious with behavior in the real world in addition to being statistically accurate.

5.1.8 Web operation Module(Flask GUI)

The system's user interface is the Flask GUI module, which enables end stoners to view the prophecy channel. It's executed using Python's Flask web frame and allows end stoners to interact with the model through an intuitive and responsive cybersurfer-predicated interface. It's possible to register and log in securely, and the login information is kept in a MySQL database. Following authentication, guests are taken to a dashboard where they can choose between two models future prophecy , which shows projected prices outside of the test set, and history date prophecy , which shows factual vs. anticipated prices(with evaluation). Using dynamic data injection, the backend obtains the demanded model labors and renders them onto HTML templates analogous as predict.html.

5.1.9 Database Module (Institutional MySQL)

This module handles the system's long-term user data storage. It comes with a MySQL database that has a user table with columns for email, password, name, and ID. Information is entered into this table by users when they register using the Flask application, and credentials are compared to previously stored data upon login. This module serves as the foundation for user authentication, session management, and the recording of usage patterns or forecasts for upcoming upgrades. It supports numerous users and acts as the foundation for account-based access to the forecast interface.

5.2 ALGORITHM

5.2.1 Facebook Prophet Algorithm

In our project, the Facebook Prophet algorithm is utilized as the primary tool for deriving long-term trends and seasonality in crude oil prices. Prophet is an open-source forecasting tool created by Facebook that is particularly tailored to handle time series data with strong seasonal effects, trend changes, and missing values. It is most appropriate for business and financial time series and is therefore perfectly suited for forecasting crude oil prices over time.

Working Principle of Prophet

Prophet is an additive model in which the time series is broken down into the following components:

$$\boldsymbol{y = g(t) + s(t) + h(t) + \in t}$$

g(t): Trend function to capture non-periodic changes.

s(t): Seasonality component (yearly, weekly, or daily trends).

h(t): Holiday effects or special events .

εt: Error term for random variations.

Prophet offers flexibility when modeling these elements and can also automatically detect changepoints, sudden changes in the trend due to external factors like policy interventions or market shocks. Some of the key features of the prophet that we have used in our is given below:

Trend Detection

Prophet captures and tracks the overall upward or downward trend of crude oil prices. It can accommodate piecewise linear or logistic growth models, depending on the nature of data.

Seasonality Modeling

Prophet uses Fourier series to identify periodic trends in the time series. In our application, it helps model quarterly or annual trends in crude oil supply and demand.

Automatic Changepoint Detection

Prophet can automatically identify changepoints in historical data where the trend radically changes, which is especially important for volatile markets like crude oil.

Dealing with Missing and Irregular Data

Missing data and outliers are elegantly handled by Prophet without requiring complex imputation or data smoothing.

Flexible Forecast Horizon

Prophet accommodates forecasting to any future interval of interest handy for short-term and long-term oil price prediction.

Simple Interpretability

Prophet provides trend visualizations, seasonality visualizations, and uncertainty interval visualizations, which help us understand the drivers of the forecast.

In our hybrid approach, Prophet is the first-stage predictor that detects macro trends. The residuals (i.e., actual minus Prophet's prediction) are then passed to the GRU model to capture short-term noise and variations. This division of labor makes the hybrid model more robust and accurate, as Prophet captures the slow-moving signals and GRU refines the prediction with short-term variations.

Advantages of Using Prophet

- Pros of Using Prophet
- Fast and scalable even with large data
- not much parameter tuning required
- automatic seasonal trend detection
- Easy to use and plays well with Python and Jupyter Notebook
- Long-term prediction is a strong suit

Facebook Prophet in our project has a strong foundation of trend analysis and long-term predictions of crude oil prices. The results are further enriched by a GRU model to generate an effective hybrid model for highly accurate and interpretable predictions.

5.2.2. Gated Recurrent Unit Algorithm (GRU)

The Gated Recurrent Unit (GRU) is utilized to handle the irregular and short-term fluctuations in crude oil prices—commonly referred to as residual oscillations—which remain after the Prophet model has extracted the long-term trends and seasonality from the time series. These residuals often reflect market noise, abrupt demand shifts, or transient volatility patterns that Prophet alone cannot capture effectively. To address this limitation, a GRU-based model is proposed, specifically trained to learn from these residuals. As part of the Recurrent Neural Network (RNN) family, GRUs are highly suitable for modeling sequential and time-dependent data. Unlike standard RNNs, which face challenges such as vanishing gradients and difficulty in learning long-term dependencies, GRUs incorporate gating mechanisms—namely the update gate and reset gate—that regulate the flow of information across time steps. This architectural advancement allows GRUs to retain and update relevant information across longer sequences without gradient degradation. By focusing on residual learning, the GRU component complements the Prophet model, enhancing the hybrid system's ability to capture both long-range patterns and short-term variability in crude oil prices. The model's strength lies in its capacity to recognize intricate dynamics in the residual data, which improves short-term forecasting accuracy.

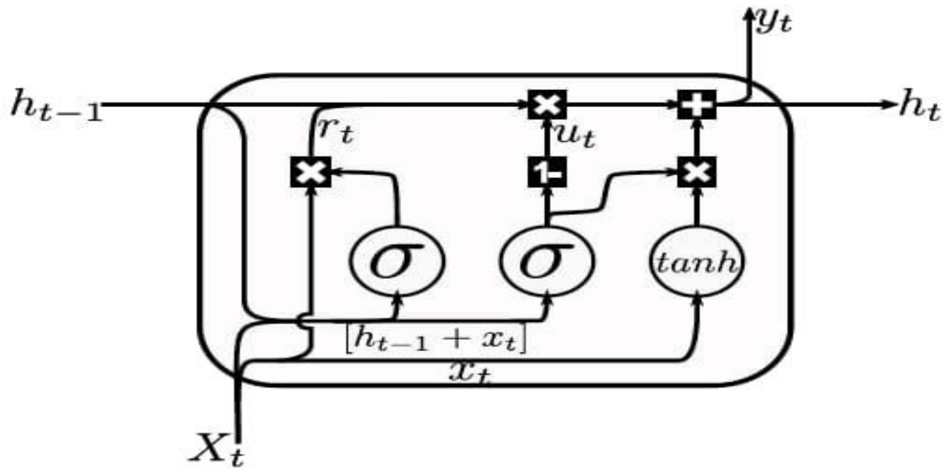

Fig 5.2.2.1: GRU Block Diagram

A GRU cell has two principal gates:

- **Update Gate:** Determines the portion of past information to carry forward, helping the model to preserve long-term dependencies.
- **Reset Gate:** Controls the extent to which previous information is forgotten, enabling the model to remain responsive to recent trends and changes in the sequence.

Update gate

$$\boldsymbol{Z_t} = \boldsymbol{\sigma}(\mathbf{W_z} \cdot [\mathbf{h_{t-1}}, \mathbf{X_t}])$$

Reset gate

$$\mathbf{r_t} = \boldsymbol{\sigma}(\mathbf{W_r}.[\mathbf{h_{t-1}}, \mathbf{X_t}])$$

Candidate activation

$$\widehat{\boldsymbol{h}}_{\boldsymbol{t}} = \boldsymbol{tanh}(\boldsymbol{W}.[\boldsymbol{r_t} * \boldsymbol{h_{t-1}}, \boldsymbol{X_t}])$$

Last memory

$$\boldsymbol{h_t} = (\mathbf{1} - \boldsymbol{z_t}) * \boldsymbol{h_{t-1}} + \boldsymbol{z_t} * \widehat{\boldsymbol{h_t}}.$$

Benefits of Applying GRU

- Efficient and easy to use for time series forecasting
- Efficiently captures short-term dependencies
- Needs fewer parameters compared to LSTM
- Ideal for large datasets because of quicker convergence
- Works well with Prophet to create a strong hybrid model

GRU is essential to improve the accuracy of our crude oil price forecasting model. By targeting the high-frequency signals that are not captured by Prophet, GRU supplements the model and assists in generating accurate and high-fidelity forecasts.

5.2.3 GWO Optimization

The social structure and hunting habits of grey wolves in the wild served as the inspiration for the development of the sophisticated metaheuristic optimization algorithm known as the Grey Wolf Optimizer (GWO). The GRU (Gated Recurrent Unit) model, which forecasts the residuals left by the Prophet model, uses GWO to optimize its hyperparameters in our hybrid crude oil price prediction project. The right choice of hyperparameters, including learning rate, number of hidden layers, number of neurons in each layer, and batch size, is critical to the performance of deep learning models like GRU. It can take a lot of time to manually adjust these parameters, and the results might not be the best. To get around this, GWO is used to automate the process of determining the best hyperparameter setup for the GRU model. The algorithm simulates the group hunting strategy and leadership hierarchy of grey wolves, with beta, delta, and omega wolves following the alpha wolf, which is the optimal solution. In order to effectively explore and exploit the search space, these wolves cooperate and adjust their positions according to the relative distance to the prey (i.e., the optimal solution). Throughout the optimization process, GWO assesses each potential solution (a collection of GRU hyperparameters) by training the GRU model with those parameters and calculating a fitness value, usually derived from a performance metric on the validation dataset like RMSE ,MAE. The wolves adjust their positions over time in order to converge on the set of parameters that performs the best. This improves the hybrid model's overall forecasting accuracy by fine-tuning the GRU model to better learn the short-term residual patterns. Our system is able to model intricate and erratic crude oil price behaviors with greater accuracy and efficiency thanks to the integration of GWO.

5.3 DATA FLOW DIAGRAM

A Data Flow Diagram (DFD) is a graphical representation used to illustrate how information moves through a system. It provides a clear and organized view of system inputs, outputs, data processing steps, and storage points. Whether the processes are manual, automated, or a combination of both, a well-structured DFD helps convey a significant portion of the system's functional requirements. It serves to define the system's boundaries and overall scope. Additionally, DFDs are useful communication tools, helping bridge the understanding between systems analysts and stakeholders involved in the system's design or redesign.

DFD Diagram

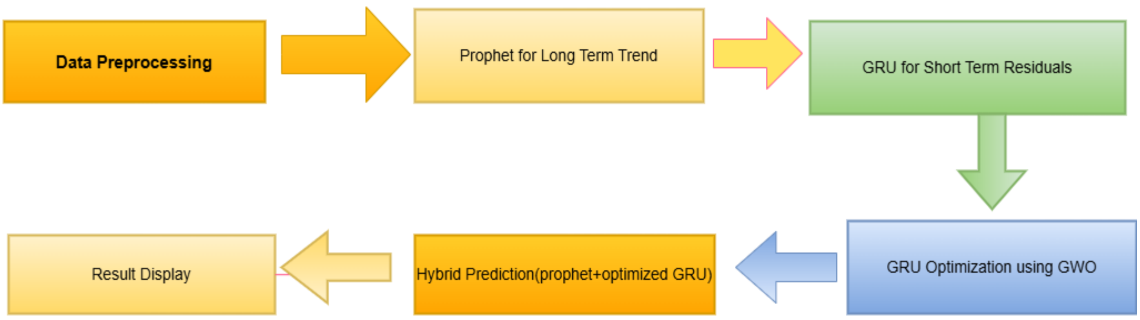

Fig 5.3.1: DFD for proposed system

5.4 UML DIAGRAMS

5.4.1 Use Case Diagram

A Use case diagram in the Unified Modeling Language (UML) is a type of behavioral diagram built by and from a Use-case analysis. Its purpose is to display a graphical illustration of the functionality provided by a system in terms of actors, their objectives (stated as use cases), and the relationships among the use cases. The main application of a use case diagram is to show what system functions are performed for what actor. System actor roles can be depicted.

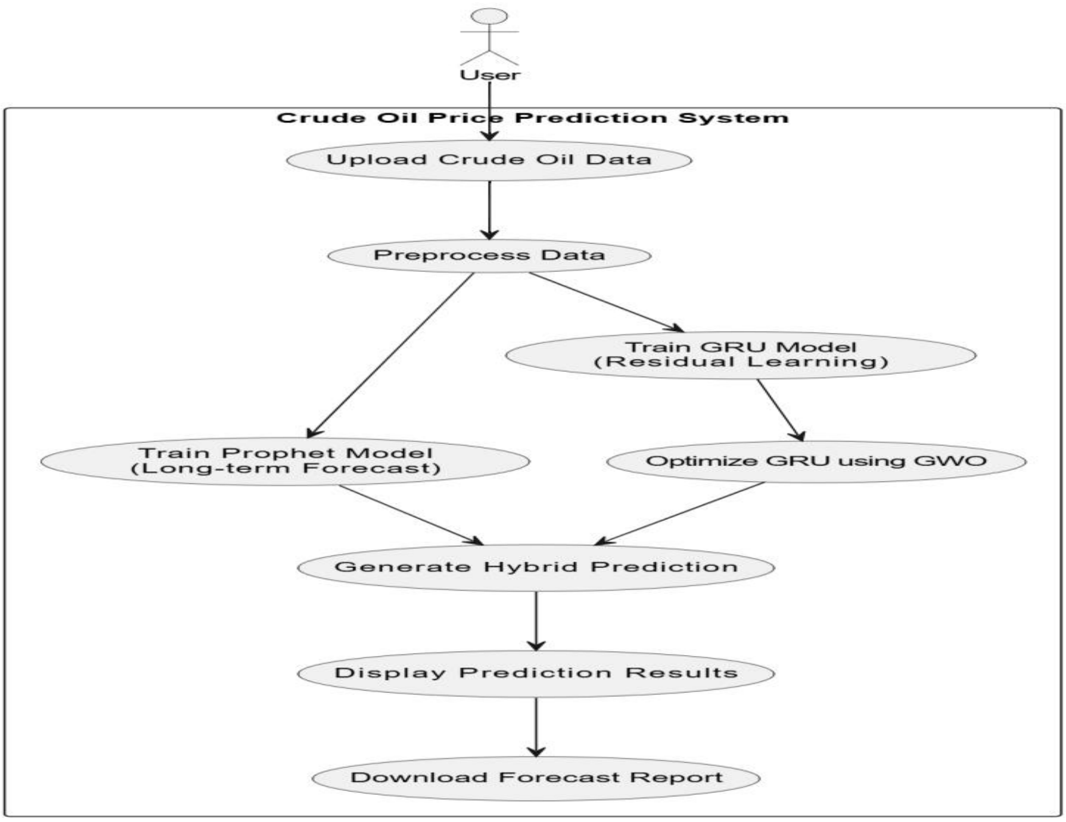

Fig 5.4.1.1: Use Case Diagram

5.4.2 Class Diagram

UML class diagram is a form of static structure diagram employed in computer programming. It schematically represents the architecture of a system through its classes, their attributes, methods (or operations), and how these interact. The diagram serves to explain the data and behaviors contained within each class and how they relate to one another in the system.

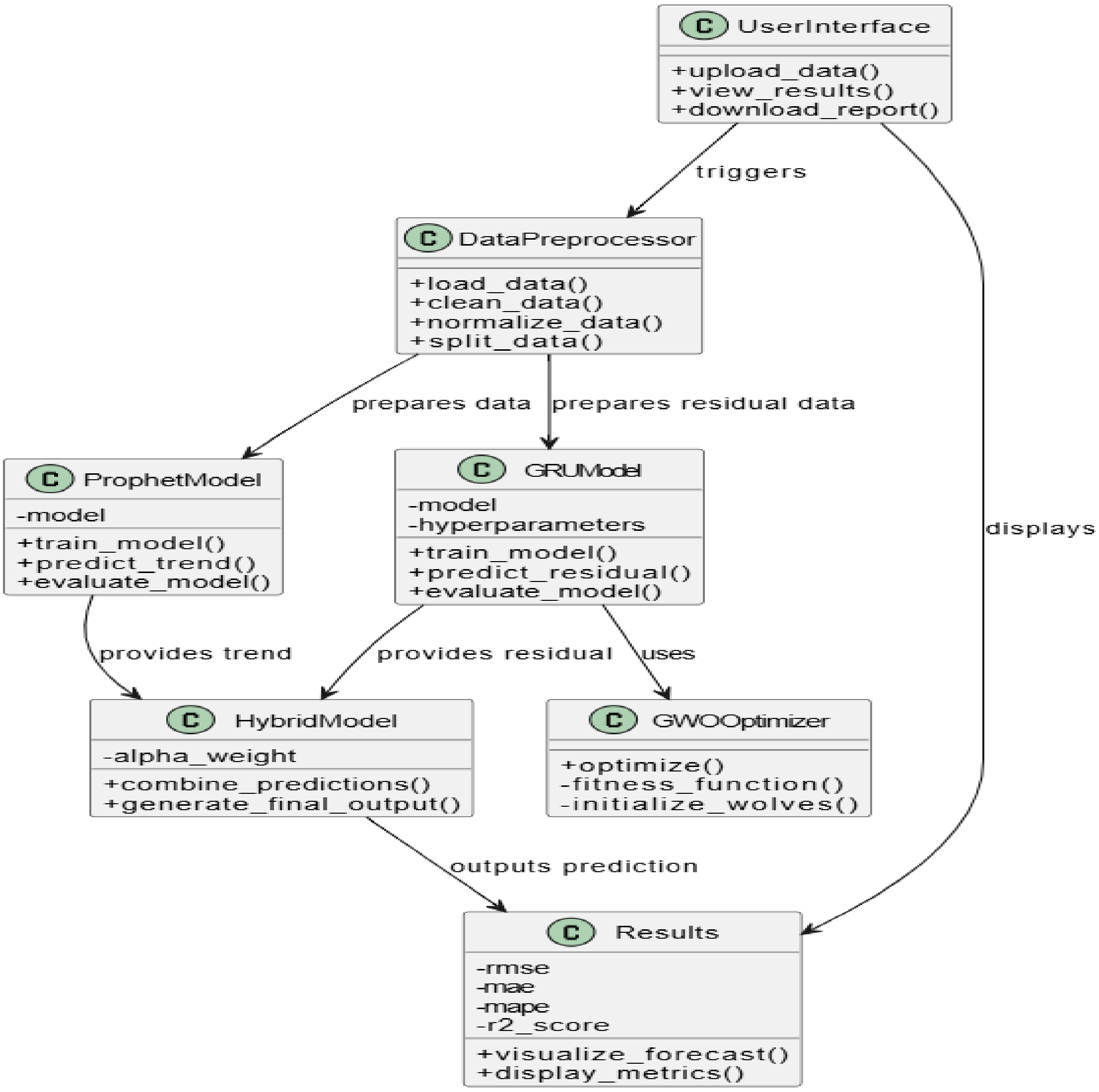

Fig 5.4.2.1: Class Diagram

5.4.3 Sequence Diagram

An object-oriented Unified Modeling Language (UML) sequence diagram is an interaction diagram that describes how objects or processes communicate with one another over time. It emphasizes the sequence in which messages are passed between them. It is a special kind of Message Sequence Chart and is also known as an event diagram, event scenario, or timing diagram.

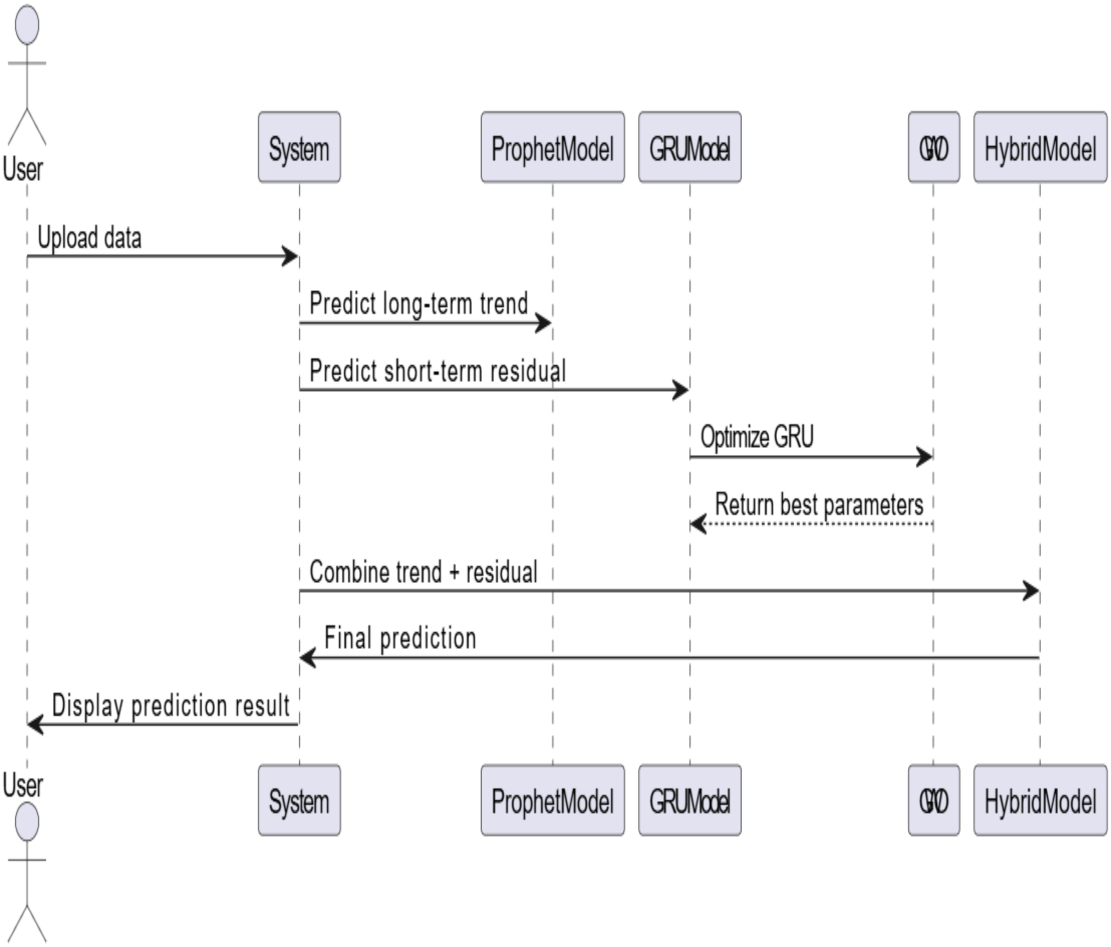

Fig 5.4.3.1: Sequence Diagram

5.4.4 Colloboration Diagram

In a collaboration diagram, the order of method calls is represented through a numbering system that shows the sequence in which methods are called. These numbers are used to illustrate the flow of communication among objects. Taking an order management system as an example, the method calls in a collaboration diagram are analogous to those in a sequence diagram. But whereas the time of their interactions is an essential concern for sequence diagrams, collaboration diagrams also reflect the structural relationships and organization of objects in the collaboration.

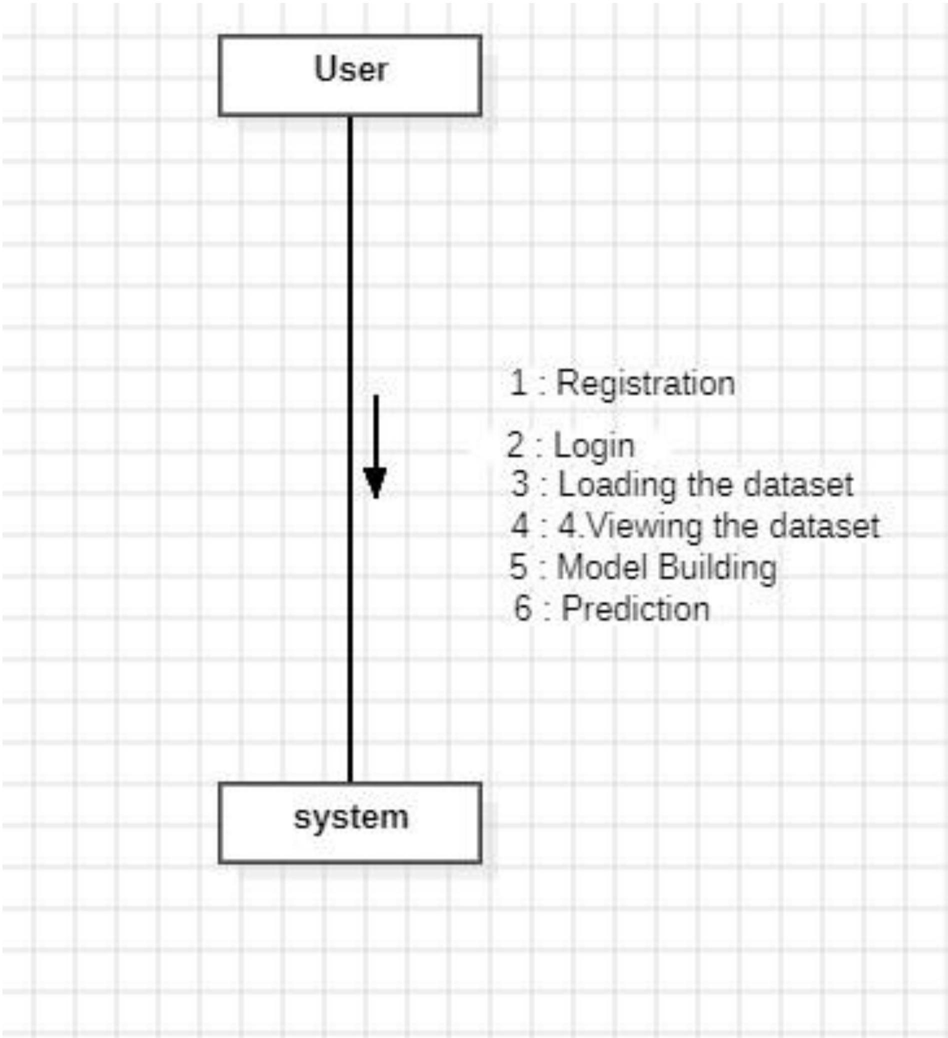

Fig 5.4.4.1: Collaboration Diagram

5.4.5 Activity Diagram

Activity diagrams are used to illustrate the flow of control or processes within a system. As part of the Unified Modeling Language (UML), they are especially effective in visualizing workflows that involve sequences, parallel actions, loops, and decision points. These diagrams are particularly helpful in capturing the dynamic behavior of subsystems and provide a clear overview of how different operations within a process are connected.

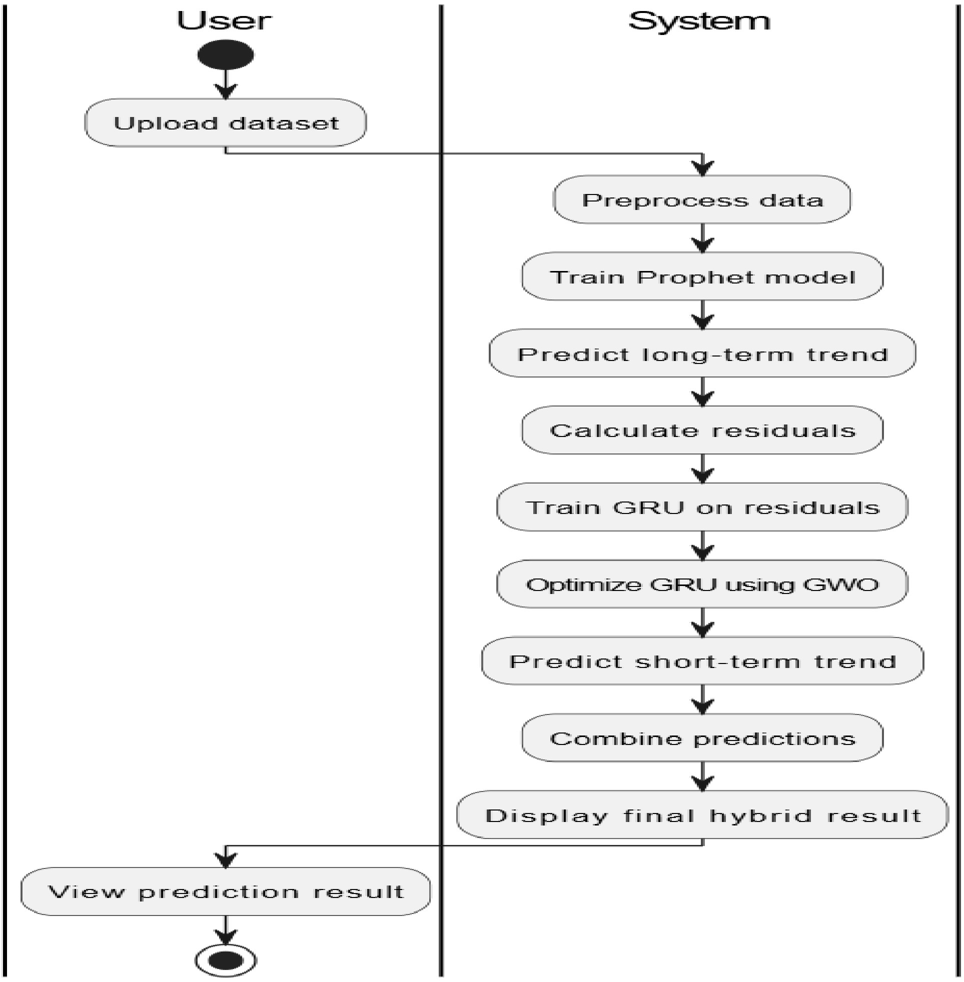

Fig 5.4.5.1: Activity Diagram

5.4.6 ER DIAGRAM:

An Entity–Relationship (ER) diagram is a visual tool used to describe the structure of a database. It outlines how various entities—typically representing tables—are related to one another, along with the attributes that define them. Each entity set contains similar objects, and their attributes represent the data fields. ER diagrams help in understanding the logical layout of a database by clearly mapping out the relationships between tables and their key components.

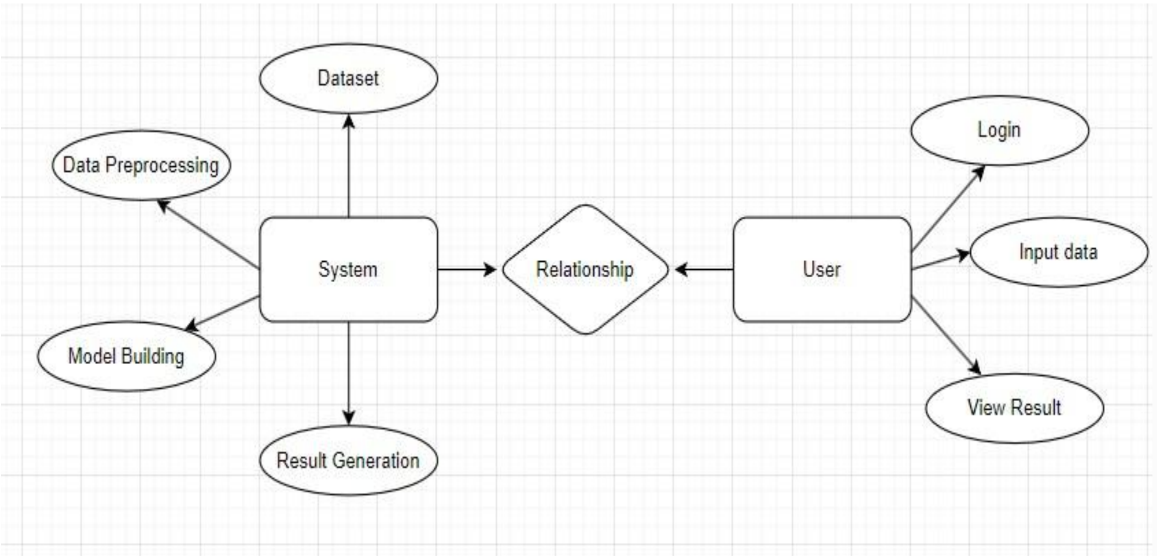

Fig 5.4.6.1: ER Diagram

5.5 INPUT DESIGN

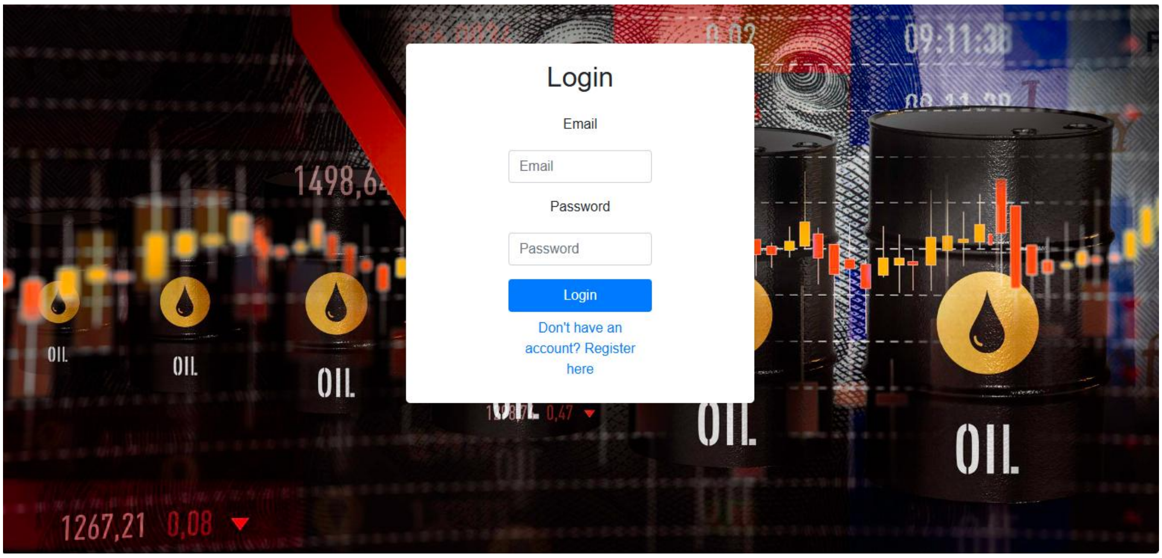

Fig 5.5.1: Input Design

5.6 OUTPUT DESIGN

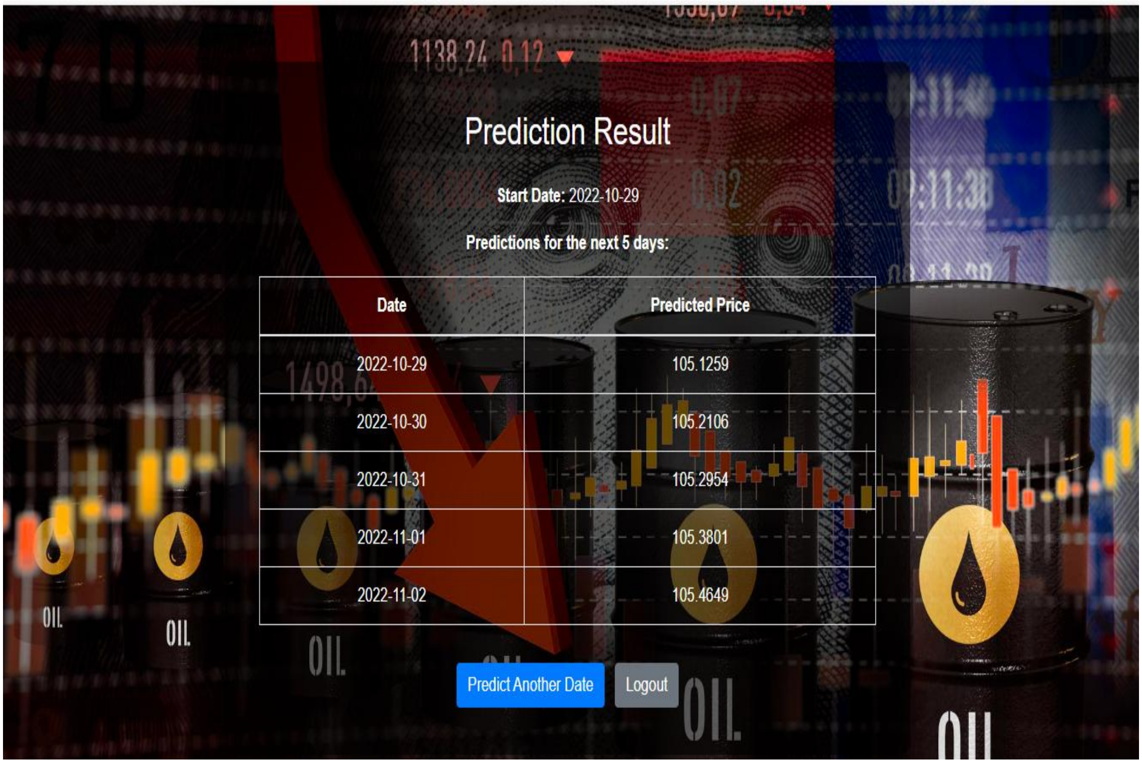

Fig 5.6.1: Output Design

CHAPTER 6
SYSTEM SPECIFICATION

6.1 SOFTWARE REQUIREMENTS

The software platform offers the appropriate programming utilities, libraries, and operating system to effectively build, train, and test the crude oil price forecast models.

Operating System	: Windows 7/8/10
Server side Script	: HTML, CSS, Bootstrap & JS
Programming Language	: Python
Libraries	: Flask, Torch, Tensorflow, Pandas, Mysql.connector
IDE/Workbench	: Jupyter Notebook, VSCode
Server Deployment	: Xampp Server
Database	: MySQL

6.2 HARDWARE REQUIREMENTS

Hardware devices are important for performing machine learning and deep learning operations effectively. The processing capacity, memory space, and storage speed directly influence data processing, model training, and real-time prediction.

Processor	: Intel i5
RAM	: 16GB
Storage	: 512GB PCIe 3.0 NVMe M.2 SSD
GPU	: NVIDIA CUDA-enabled for deep learning

CHAPTER 7

SYSTEM TESTING

7.1 DEFINITION OF TESTING

Testing is a crucial aspect of software development that aims to reveal any latent flaws in the application. It entails thoroughly examining the system for possible bugs, logic errors, or integration faults. Testing verifies whether the software works properly and satisfies both functional and non-functional specifications defined by the client or users. This process guarantees that every component or module functions as designed and that the entire system functions as designed under various conditions. It ensures that it provides a stable and reliable end product.

7.2 TESTING LEVELS

7.2.1 Unit Testing

Unit testing was conducted for standalone modules such as the data preprocessing pipeline, Prophet model forecast, GRU-based residual learning, and hybrid output combination function. Each function was tested with valid and edge-case inputs to ensure control flow, output types, and handling of data. Unit tests were implemented using Python's `unittest` module. This level enabled early detection of logic issues or erroneous model outputs.

7.2.2 Integration Testing

Integration testing helped to validate good interaction among modules like Prophet model and GRU, as well as the user interface and the prediction engine. The hybrid combined prediction logic was tested for coherence in passing residuals and recombining the forecast. The handling of uploaded CSVs and dynamic user input to make predictions about future dates was also tested.

Test Result: All the integrated modules interacted properly, and the system generated proper combined forecasts.

7.2.3 User Acceptance Testing (UAT)

User Acceptance Testing was performed to ensure the prediction system satisfies user needs and is easy to use. Real-time situations like uploading custom data sets, choosing prediction ranges, and observing graphical or tabular output were tested.

Outcome: All acceptance tests were passed successfully, and the system functioned without any critical faults.

7.2.4 Functional Testing

The system was tested to ensure all features functioned as specified. Key areas were:

Valid Input: Verified valid CSV files, date ranges, and model parameters were accepted.

Invalid Input: Verified graceful handling of empty files, invalid dates, or corrupted CSVs.

Functional Accuracy: Every aspect from model training to GUI output was checked against the specifications.

Correct Output: The system produced anticipated forecasts for various test inputs.

White Box Testing

White box testing was employed to check internal logic such as residual extraction from Prophet output, correctness of GRU model training loop, and alpha-weighted prediction integration.

Black Box Testing

Testers tested the system from a user's point of view without seeing internal code. Different CSV files, date ranges, and prediction parameters were employed to verify output accuracy.

Testing Objectives

1. All input fields must accept correct data.
2. Navigation and submission in the GUI must work as expected.
3. System messages must display clearly and correctly.
4. Uploaded data must be parsed and displayed correctly.

Validation Points

1. Correct formatting of inputs (e.g., date, CSV format).
2. Avoidance of duplicate submissions or null values.
3. Output should match the chosen parameters and uploaded file.

Test Cases

INPUT	OUTPUT	RESULT
Inputs provided on different modules (prophet, GRU, hybrid).	Correct individual and hybrid forecast.	Success
Forecast results using custom csv and different start dates.	Consistent and realistic future values.	Success

Table1: Test Cases

Test cases Model building

S.NO	Test cases	Input	Expected Output	Actual Output	P/F
1	Read the dataset	Default or uploaded CSV file.	Datasets should be loaded with relevant columns (Date,Price, etc).	Dataset loaded and validated.	P
2	Preprocess the input data	Dataset columns with missing values or extra spacess.	Cleaned and formatted data ready for modeling.	Data cleaned successfully.	P

3	Prophet model forecast.	Cleaned data and forecast range.	Trend component generated without errors.	Prophet forecast returned correct ttrend.	P
4	GRU model training on residuals.	Residuals extracted from prophet outpt.	GRU model should learn residual pattern.	Model trained with decreasing loss.	P
5	Hybrid output generation.	Prophet + GRU output with alpha weight.	Combined output with improved accuracy.	Hybrid forecast generated as expected.	P
6	Prediction on provided data.	Test data	Model processes user input and shows prediction.	Custom data handled correctly.	P
7	Display GUI results.	Predicted values.	Display in tabular format with dates and graphs.	GUI renders table accurately.	P

Table 2: Test cases Model Building

CHAPTER 8
SYSTEM IMPLEMENTATION

8.1 SYSTEM IMPLEMENTATION

8.1.1 Data Collection

The project's data collection procedure entails compiling historical crude oil prices from reliable financial data sources spanning multiple decades. Important financial characteristics that are necessary for capturing the trend and variations in oil prices are included in the dataset, including Date, Open, High, Low, Close, Volume. The model can learn from a wide range of market conditions, including economic booms and recessions, thanks to the data's long time span, which increases the accuracy of future projections

8.1.2 Data Preprocessing

To make sure the dataset is clean and appropriate for modeling, data preprocessing is done after the raw data is gathered. This entails detecting and eliminating outliers that might skew the model's learning, handling missing values with suitable methods like interpolation or forward-filling, and appropriately formatting all date fields. In order to capture temporal dependencies, feature engineering is used to generate moving averages or lag-based features. In order to facilitate faster convergence during the training of deep learning models like GRU, normalization is also applied to the numerical columns, bringing all values within a similar scale.

8.1.3 Model Training

The project's training phase employs a two-stage hybrid modeling methodology. First, long-term trends and seasonal patterns in oil prices are identified and predicted using the Facebook Prophet model. Prophet generates a baseline prediction and residuals while efficiently capturing daily, weekly, and annual seasonality. A GRU (Gated Recurrent Unit) model is then trained using these residuals, which stand for transient variations that Prophet was unable to detect. As a recurrent neural network designed for sequential data, GRU efficiently learns the residual patterns. The Grey Wolf Optimizer (GWO), an optimization algorithm inspired by nature, is used to fine-tune hyperparameters in order to improve the performance of the GRU.

8.1.4 Model Evaluation

Following training, the models' forecasting accuracy is assessed both separately and collectively. While the GRU model is evaluated for its ability to predict the residuals, the Prophet model is evaluated for its ability to capture trend and seasonality. Both outputs are combined using a weighted summation method in the final hybrid model. To give a quantitative picture of the quality of the predictions, evaluation metrics like MAE, RMSE, MAPE, and R2 are calculated on the test dataset. These metrics verify whether the hybrid approach produces better results than standalone models and enable comparison with other models.

8.1.5 Model Saving

The trained GRU model, the Prophet configuration, and preprocessing elements like scalers are serialized and saved to disk after the hybrid model produces results that are satisfactory. Formats like `.keras` for GRU and `.gz` for scalers are used for this. Real-time forecasting in the web application is supported by saving the model's components, which guarantees that future predictions can be made without retraining the model.

8.1.6 Model Prediction

Users can obtain crude oil price forecasts by uploading data files or entering a range of dates. The Prophet model is used to calculate long-term trends and residuals after the uploaded or chosen data has been preprocessed using the scalers and formats that have been saved. The final hybrid prediction is produced by combining the Prophet forecast with the short-term residuals predicted by the GRU model using the optimized alpha weight. Both numerical output and graphical plots comparing the actual and predicted values are used to present the results.

8.2 USER IMPLEMENTATION

8.2.1 Login

By providing their name, email address, and password, new users can create an account through the User Registration feature. User credentials are safely saved in a MySQL database after successful registration, facilitating subsequent logins. By comparing their login information with the database, registered users can gain access to the system. Only users who have successfully authenticated can access the application's prediction section thanks to proper session handling.

8.2.2 Upload Data

After logging in, users are taken to the Prediction interface, where they can choose a future date to view projected crude oil prices or enter a historical date to compare actual and predicted prices. To provide precise price predictions for the given date, the system employs a hybrid model that combines Prophet and GRU residuals.

8.2.3 View Results

The predicted value is shown on the View Results page after predictions have been made. The system also displays the current price of crude oil for comparison if the date you have chosen is in the past. A performance graph that compares the model's expected and actual performance is also displayed, which aids users in understanding the accuracy and behavior of the model.

8.2.4 Logout

Lastly, the Logout function safely ends the user session and takes them back to the login screen. This protects the privacy of the data and limits access to the prediction system after the session is over.

CONCLUSION

We created a hybrid method for crude oil price forecasting by integrating Prophet and GRU model strengths in this project. The Prophet model identified long-term trends and seasonality, and the GRU model forecasted short-term fluctuations using the residuals of the Prophet model. This two-model method enabled us to utilize both long-term prediction and short-term volatility modeling, thus making it effective for sophisticated time-series data such as crude oil prices. With data acquisition, preprocessing, and model training, we constructed a strong system that was tuned via hyperparameter optimization and assessed via metrics such as RMSE, MAE, MAPE, and R^2. The outcomes showed better prediction performance than isolated models, stressing the power of unifying long-term trend prediction with short-term residual modeling. This hybrid model not only delivers a precise and explainable solution to crude oil price forecasting but also has potential room for improvement with sophisticated optimization, feature engineering, and more data sources, thus as a powerful tool for decision-making in the energy industry, financial markets, and finance-related sectors.

FUTURE ENHANCEMENTS

Future improvements for this crude oil price forecasting project can involve adding more features like geopolitical events, supply-demand analysis, weather conditions, and economic indicators to make the model more complete. Investigating more sophisticated machine learning models such as LSTM or Transformer-based models can enhance the model's capacity to learn long-term dependencies. Exploring other optimization methods or mixed models, for example, GRU with XGBoost or Random Forest residual error correction, might further enhance performance. Using more sophisticated hyperparameter optimization methods, such as Bayesian optimization or AutoML, would further tune the parameters to make more accurate forecasts. Further, real-time data incorporation, e.g., live market prices and news feeds, would allow dynamic forecasting. Applying ensemble techniques such as stacking or bagging may provide increased accuracy from combining the benefits of several different algorithms. Providing increased model explainability through such methods as SHAP or LIME would promote transparency, which would enable stakeholders to comprehend decision-making logic. Facilitating greater user interface such as enabling visualization of data, trend analysis, and future price simulation may lead to improved usability. Enhancing model resilience to deal with extreme market conditions and integrating global market data for more extensive price forecasting would make the system more robust and thorough. These improvements would make the crude oil price forecasting system more accurate, flexible, and beneficial in real-world usage, specifically in trading, investment, and market analysis.

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APPENDIX

A.SOURCE CODE:

Frontend.py

```
from flask import Flask, render_template, request, redirect, url_for, session
from prophet import Prophet
from tensorflow.keras.models import load_model
import pymysql, pandas as pd, numpy as np, joblib
from werkzeug.security import generate_password_hash, check_password_hash

app = Flask(__name__)
app.secret_key = 'your_secret_key'

# Load everything
model =
load_model("D:/projectcrude/crude_oil_forecasting/models/gru_residual_model.keras")
scaler = joblib.load("D:/projectcrude/crude_oil_forecasting/models/residual_scaler.gz")
df = pd.read_csv("D:/projectcrude/static/Crude oil.csv")
df['ds'], df['y'] = pd.to_datetime(df['Date']), df['Close/Last']
prophet = Prophet(); prophet.fit(df[['ds', 'y']])

def get_db():
    return pymysql.connect(host='localhost', user='root', password='',
database='crude_oil_prediction')

@app.route('/')
def home(): return render_template('home.html')

@app.route('/register', methods=['GET', 'POST'])
def register():
    if request.method == 'POST':
        name, email, pwd = request.form['name'], request.form['email'],
request.form['password']
        hashed = generate_password_hash(pwd)
        try:
```

```
            con = get_db(); cur = con.cursor()
            cur.execute("INSERT INTO user (name, email, password) VALUES (%s, %s,
%s)", (name, email, hashed))
            con.commit(); con.close(); return redirect(url_for('login'))
        except Exception as e: return f"Registration error: {e}"
    return render_template('register.html')

@app.route('/login', methods=['GET', 'POST'])
def login():
    if request.method == 'POST':
        email, pwd = request.form['email'], request.form['password']
        try:
            con = get_db(); cur = con.cursor()
            cur.execute("SELECT * FROM user WHERE email=%s", (email,))
            user = cur.fetchone(); con.close()
            if user and check_password_hash(user[3], pwd):
                session['user'] = user[1]; return redirect(url_for('predict'))
            return render_template('login.html', error='Invalid credentials')
        except Exception as e: return f"Login error: {e}"
    return render_template('login.html')

@app.route('/logout')
def logout(): session.pop('user', None); return redirect(url_for('home'))

@app.route('/predict', methods=['GET', 'POST'])
def predict():
    if 'user' not in session: return redirect(url_for('login'))
    if request.method == 'POST':
        date_str = request.form['date']
        target_date = pd.to_datetime(date_str)
        try:
            df_res = pd.read_csv("final_hybrid_predictions.csv")
            df_res['Date'] = pd.to_datetime(df_res['Date'])
            if target_date in df_res['Date'].values:
```

```
            row = df_res[df_res['Date'] == target_date].iloc[0]
            return render_template('predict_result.html', date=target_date.date(),
                                   predicted=row['Hybrid_Prediction_Weighted'],
                                   actual=row['Actual'],
error=abs(row['Hybrid_Prediction_Weighted'] - row['Actual']),
                                   future=False)
        if target_date > df['ds'].max():
            days = (target_date - df['ds'].max()).days
            trend = prophet.predict(prophet.make_future_dataframe(days))['trend'].iloc[-
1]
            df['y_trend'] = prophet.predict(df[['ds']])['trend']
            df['y_residual'] = df['y'] - df['y_trend']
            last_60 = df['y_residual'].values[-60:]
            scaled_input = scaler.transform(last_60.reshape(-1, 1)).reshape(1, 60, 1)
            residual = model.predict(scaled_input)[0][0]
            pred = trend + 1.05 * scaler.inverse_transform([[residual]])[0][0]
            return render_template('predict_result.html', date=target_date.date(),
                                   predicted=pred, actual=None, error=None, future=True)
        return render_template('predict.html', error="No prediction for this date.")
    except Exception as e: return f"Prediction error: {e}"
  return render_template('predict.html')

if __name__ == '__main__':
  app.run(debug=True)
```

Backend.py:

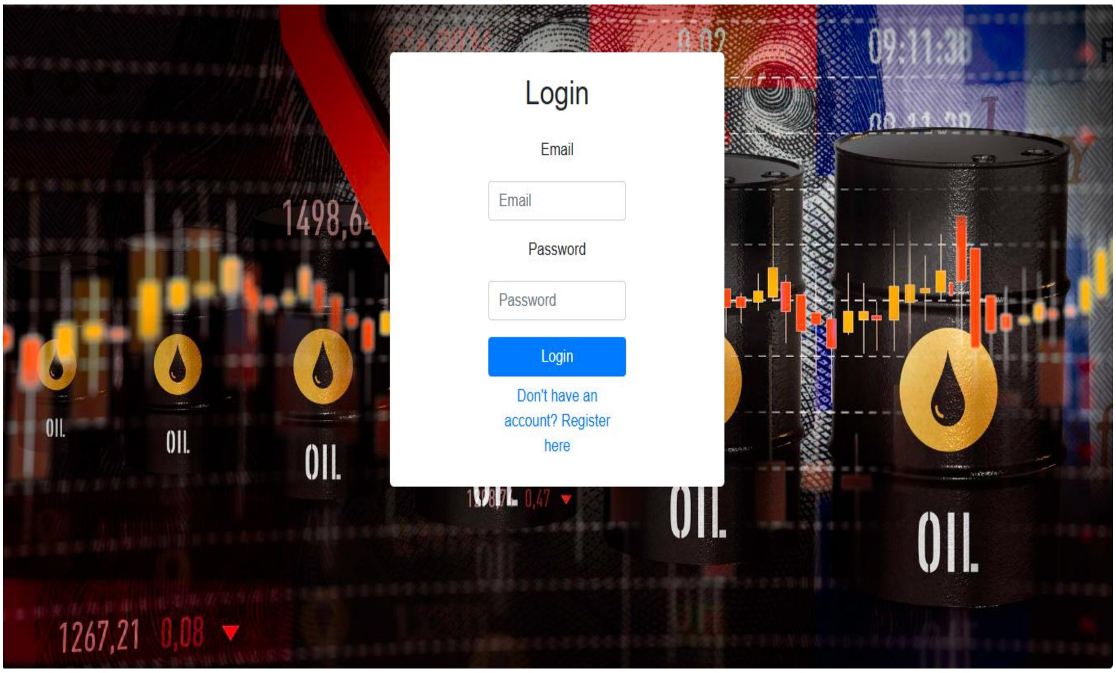
```
import pandas as pd, numpy as np, joblib
from sklearn.preprocessing import MinMaxScaler
from prophet import Prophet
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import GRU, Dense, Dropout, Input
from tensorflow.keras.optimizers import Adam
from sklearn.metrics import mean_squared_error
from mealpy.swarm_based import GWO
```

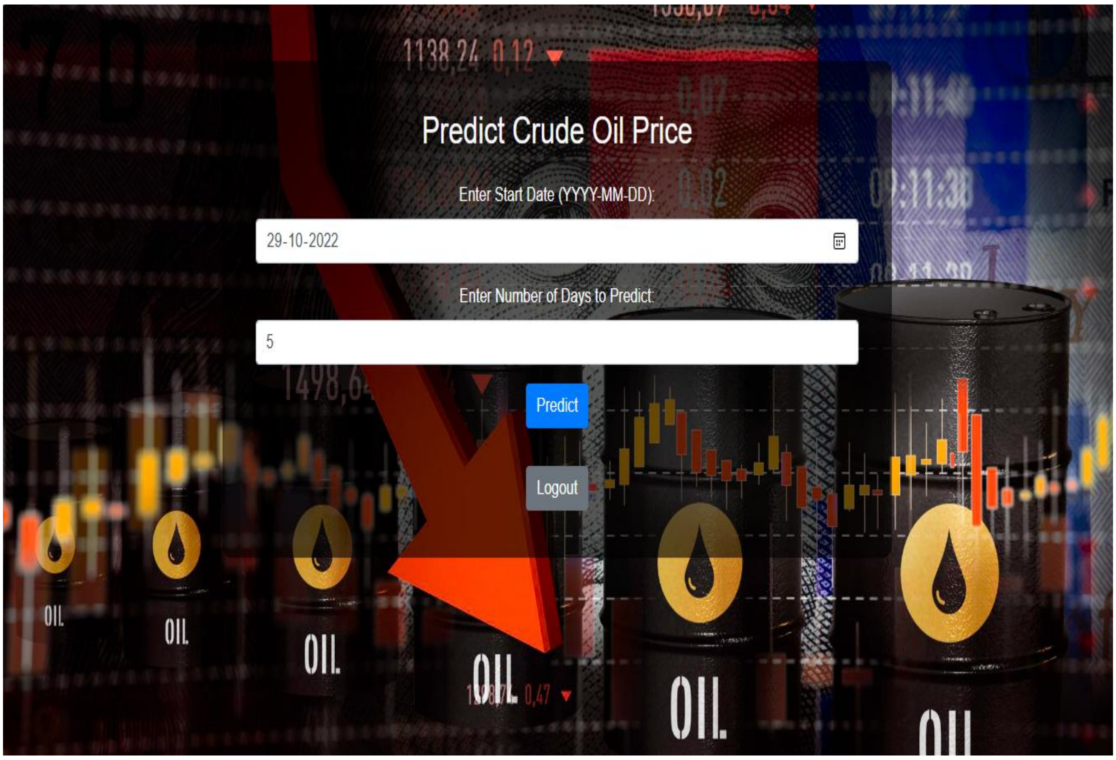
```
from mealpy.utils.problem import Problem
from mealpy.utils.space import IntegerVar, FloatVar
import matplotlib.pyplot as plt

# Load & preprocess data
df = pd.read_csv("D:/projectcrude/static/Crude oil.csv")
df['ds'], df['y'] = pd.to_datetime(df['Date']), df['Close/Last']
scaler = MinMaxScaler()
df['y'] = scaler.fit_transform(df[['y']])
joblib.dump(scaler, "crude_oil_forecasting/models/residual_scaler.gz")

# Prophet trend
prophet = Prophet()
prophet.fit(df[['ds', 'y']])
df['y_trend'] = prophet.predict(df[['ds']])['trend']
df['y_residual'] = df['y'] - df['y_trend']

# Sequence preparation
def create_seq(data, steps=60):
    return np.array([data[i-steps:i] for i in range(steps, len(data))]), np.array(data[steps:])

X, y = create_seq(df['y_residual'].values)
X = X.reshape((X.shape[0], X.shape[1], 1))
split = int(0.8 * len(X))
X_train, y_train, X_test, y_test = X[:split], y[:split], X[split:], y[split:]

# Objective for GWO
def optimize_gru(params):
    u1, u2, drop, lr, batch = int(params[0]), int(params[1]), params[2], params[3],
int(params[4])
    model = Sequential([
        Input((60, 1)), GRU(u1, return_sequences=True),
        Dropout(drop), GRU(u2), Dropout(drop),
        Dense(25), Dense(1)
```

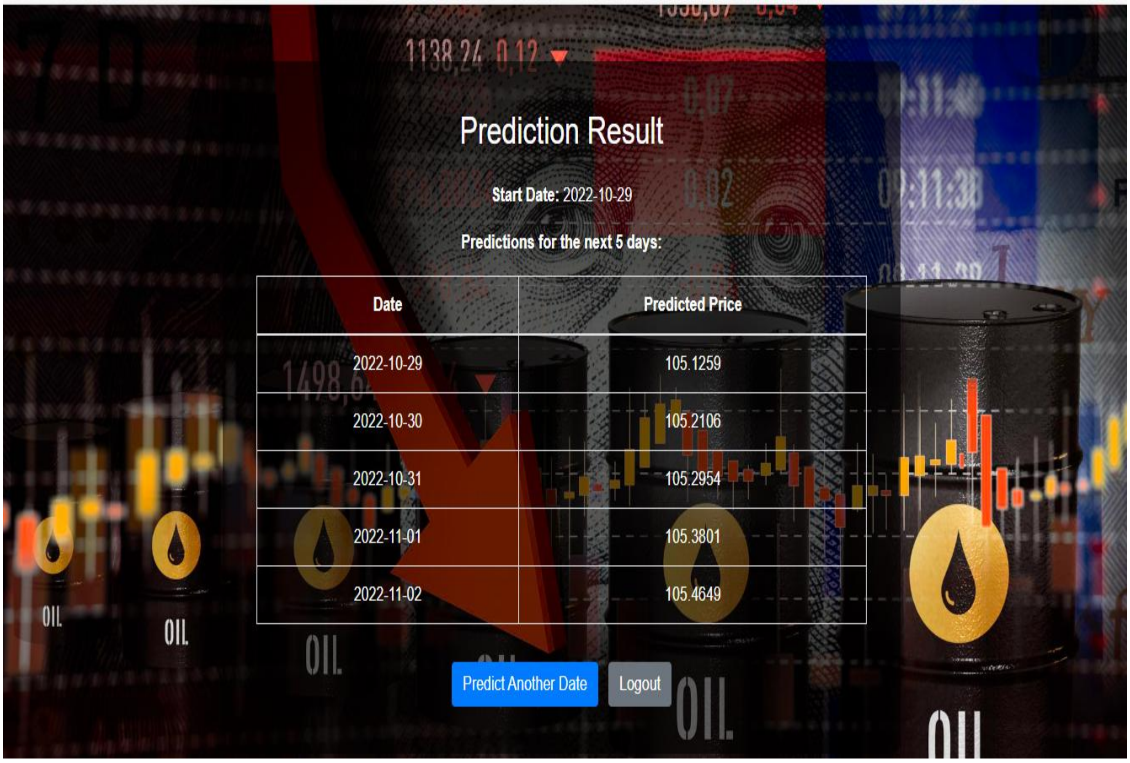
```
    ])
    model.compile(optimizer=Adam(lr), loss='mse')
    model.fit(X_train, y_train, epochs=10, batch_size=batch, verbose=0)
    pred = model.predict(X_test)
    return np.sqrt(mean_squared_error(scaler.inverse_transform(y_test.reshape(-1, 1)),
                            scaler.inverse_transform(pred)))

# GWO Optimization
space = [IntegerVar(32, 128), IntegerVar(32, 128), FloatVar(0.1, 0.4), FloatVar(1e-4, 1e-2), IntegerVar(16, 128)]
problem = Problem(obj_func=optimize_gru, bounds=space, minmax='min')
gwo = GWO.OriginalGWO(epoch=10, pop_size=5)
best = gwo.solve(problem)
u1, u2, drop, lr, batch = map(lambda x: int(x) if isinstance(x, float) and x.is_integer() else x, best.solution)

# Train final GRU
model = Sequential([
Input((60, 1)), GRU(int(u1), return_sequences=True),
    Dropout(drop), GRU(int(u2)), Dropout(drop),
    Dense(25), Dense(1)
])
model.compile(optimizer=Adam(lr), loss='mse')
model.fit(X_train, y_train, epochs=50, batch_size=int(batch), validation_data=(X_test, y_test), verbose=1)
model.save("crude_oil_forecasting/models/gru_residual_model.keras")

# Final hybrid predictions
res_pred = model.predict(X_test).flatten()
residuals_inv = scaler.inverse_transform(res_pred.reshape(-1, 1)).flatten()
trend = df['y_trend'].values[-len(res_pred):]
hybrid = trend + 0.9 * residuals_inv
actual = scaler.inverse_transform(df['y'].values[-len(res_pred):].reshape(-1, 1)).flatten()
```

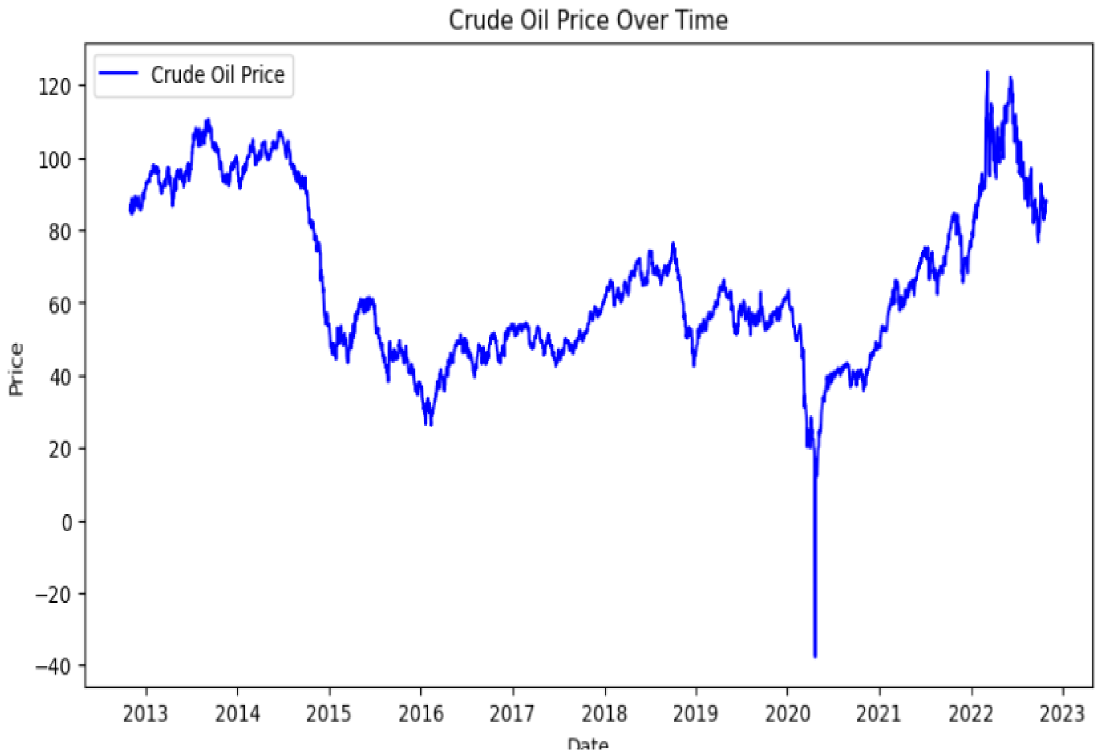
```
# Save results
results = pd.DataFrame({
    'Date': df['ds'].values[-len(res_pred):],
    'Actual': actual,
    'Prophet_Trend': trend,
    'GRU_Residual': residuals_inv,
    'Hybrid_Prediction_Weighted': hybrid
})
results.to_csv("final_hybrid_predictions.csv", index=False)
print(" Optimized hybrid predictions saved.")
```

B. SCREEN SHOTS:

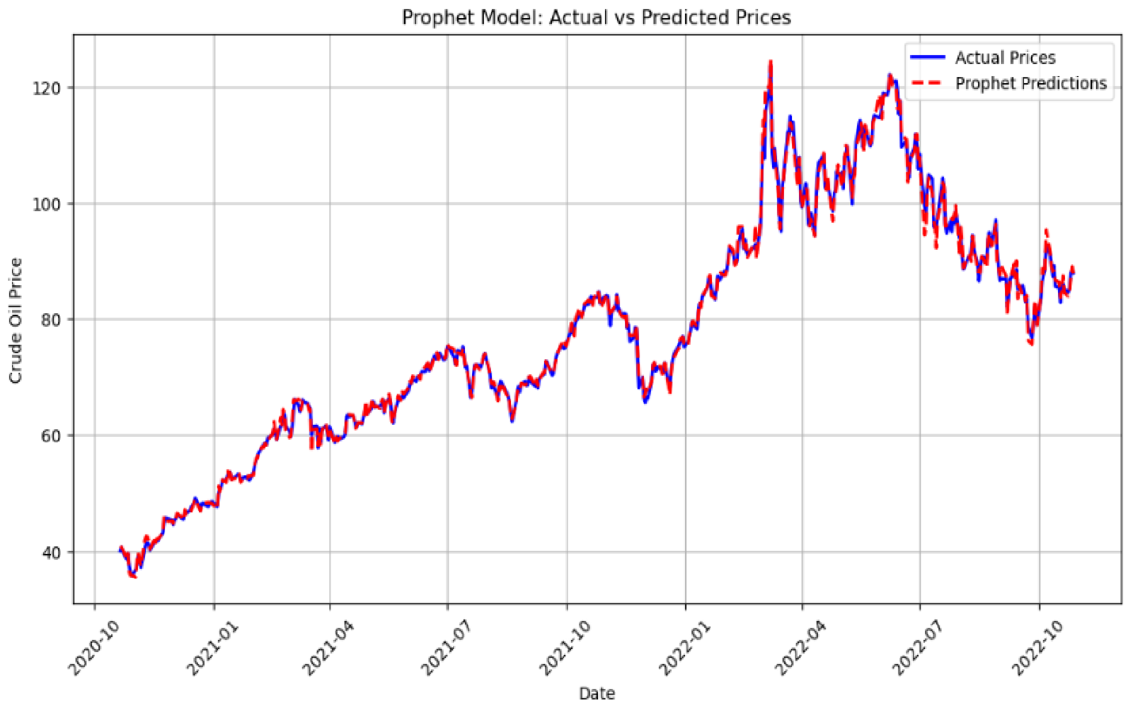



Predict Crude Oil Price
Enter Start Date (YYYY-MM-DD):
29-10-2022
Enter Number of Days to Predict:
5
Predict
Logout

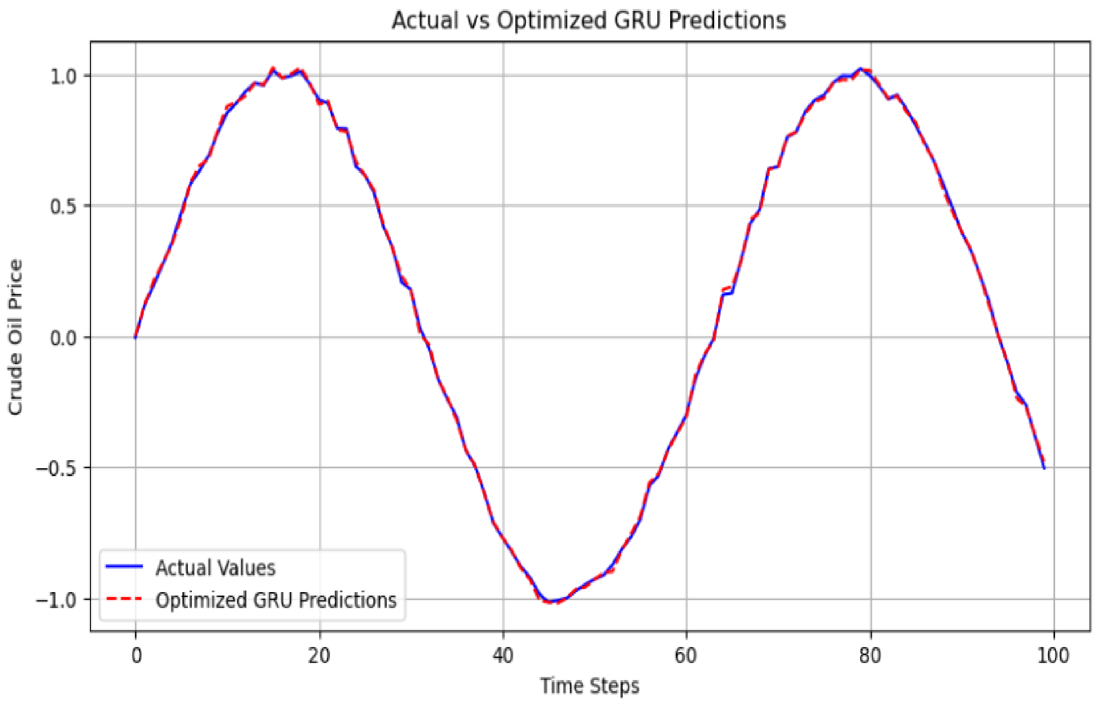

Prediction Result
Start Date: 2022-10-29
Predictions for the next 5 days:
Date
Predicted Price
2022-10-29
105.1259
2022-10-30
105.2106
2022-10-31
105.2954
2022-11-01
105.3801
2022-11-02
105.4649
Predict Another Date
Logout

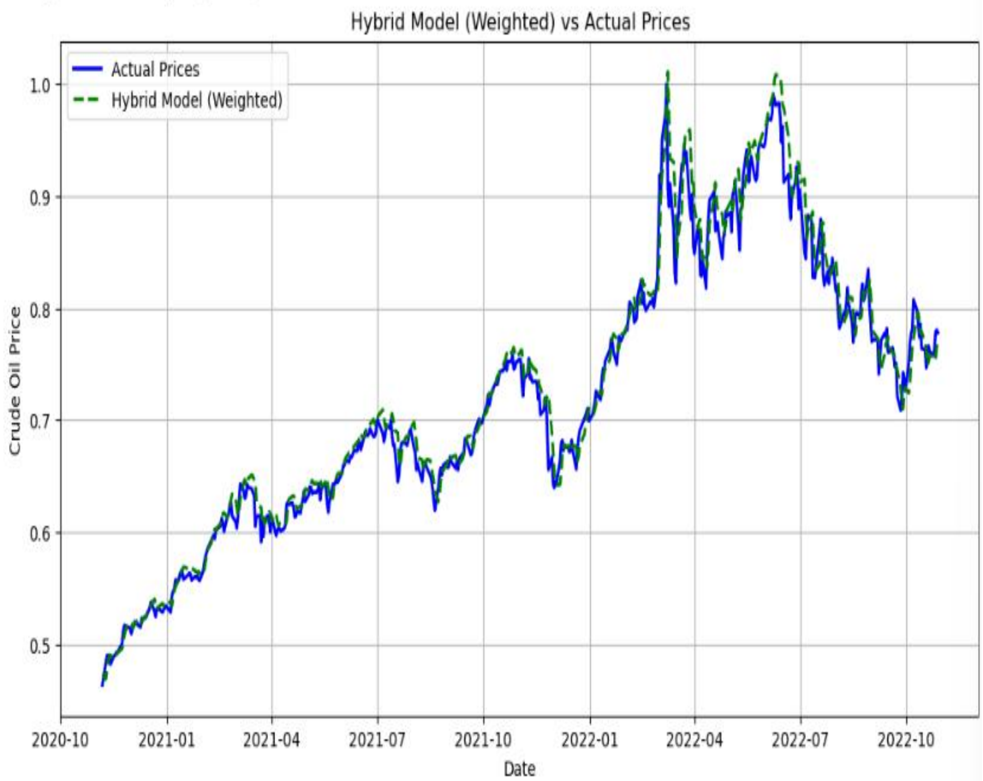


Crude Oil Price Over Time
Crude Oil Price
Price
Date



Prophet Model: Actual vs Predicted Prices
Actual Prices
Prophet Predictions
Crude Oil Price
Date


Actual vs Optimized GRU Predictions
Crude Oil Price
Time Steps
Actual Values
Optimized GRU Predictions
1.0
0.5
0.0
−0.5
−1.0
0
20
40
60
80
100


Hybrid Model (Weighted) vs Actual Prices
Actual Prices
Hybrid Model (Weighted)
Crude Oil Price
Date
1.0
0.9
0.8
0.7
0.6
0.5
2020-10
2021-01
2021-04
2021-07
2021-10
2022-01
2022-04
2022-07
2022-10

ANNEXURE

Hybrid Approach For Crude oil price prediction using prophet and gru

ORIGINALITY REPORT

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CRUDE OIL PRICE HYBRID FORECASTING USING PROPHET AND GRU

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ABSTRACT

Forecasting the price of crude oil is essential for risk management, financial decision-making, and economic planning. In order to estimate crude oil prices, we provide a hybrid forecasting model in this paper that combines the Prophet model with optimized Gated Recurrent Units (GRU). While the GRU model is used to simulate short-term price fluctuations, the prophet model is intended to identify seasonal patterns and long-term trends in pricing data. Grey Wolf Optimization (GWO) is used for hyper parameter adjustment in order to maximize the GRU model's performance. In order to improve prediction accuracy, the hybrid strategy combines long-term and short-term forecasting capabilities, utilizing the complimentary characteristics of both models. Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R2 Score among the common metrics used to assess the performance of the suggested model. This study demonstrates how integrating contemporary machine learning techniques with conventional time series forecasting approaches might enhance energy market price prediction.

Keywords: Crude Oil Price Prediction, Hybrid Forecasting Model, Prophet Model, Gated Recurrent Unit (GRU), Grey Wolf Optimization (GWO), Time series Forecasting, Hyper parameter Optimization, Machine Learning in Energy Markets, Long-Term Trend Forecasting, Short-Term Price Fluctuations, Predictive Analytics, Forecasting Accuracy, Financial Modeling, Time Series Analysis.

I. INTRODUCTION

An accurate crude oil price forecast is crucial for a number of stakeholders, including investors, legislators, and energy companies. Crude oil is a basic resource that powers global transportation, industry, and energy generation. Crude oil plays an important role in maintaining the stability of the world economy, therefore even slight changes in price can have a big impact. These wings have an effect on trade balances, interest rates, and inflation rates, which in turn have an impact on consumer spending, business financial planning, and national economies. It is impossible to overestimate the significance of precise crude oil price forecasting since it aids in risk mitigation for companies, the implementation of well-informed laws by legislators, and the optimization of financial strategies by investors. However, because of the market's volatility, the impact of outside variables like supply-demand imbalances and geopolitical events, and the intrinsic non-linear correlations in time-series data, predicting the price of crude oil is still a very difficult and complex operation. The Autoregressive Integrated Moving Average (ARIMA) model and Exponential Smoothing are two statistical models that have historically been widely accepted as the gold standard for time-series forecasting. These model's ability to accurately depict linear trends and fundamental seasonal patterns has given price forecasting a solid basis. Nevertheless, real-world financial time-series data, especially those pertaining to crude oil prices, show extremely dynamic behaviors that are marked by intricate dependencies, cyclical tendencies, and sudden changes. These complex patterns are frequently difficult for traditional statistical approaches to handle, which results in less than ideal forecasting accuracy. New avenues for getting around these restrictions have been made possible by recent development in deep learning and machine learning. Specifically, deep learning architectures like Gated Recurrent Units (GRU) have shown great promise in identifying long-range correlations in time-series data and learning temporal dependencies. GRU models successfully manage non-linearity, adjust to variable-length sequences, and mitigate the vanishing gradient issue in recurrent architectures, thereby addressing important issues that previous techniques have encountered. [1]

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In this paper, we examine the application of a hybrid forecasting model for crude oil price prediction that combines Prophet and GRU. [2] Facebook created the Prophet model, which is well known for its capacity to predict time-series data by breaking it down into trend, seasonality, and holiday effects. It is the best option for capturing more extensive price patterns in crude oil price forecasting since it excels at simulating long-term trends and market movements. However, GRU, a potent recurrent neural network variation, is very good at catching short-term oscillations because it can learn sequential dependencies in time-series data. BY merging these two models, we take advantage of their respective advantages: GRU's skill in identifying short-term volatility and Prophet's ability to capture macroeconomic trends. [3] We use Grey Wolf Optimization (GWO), a nature-inspired optimization approach that adjusts the GRU model's hyper parameters to further improve the forecasting accuracy of our hybrid model. Grey Wolf hunting and social hierarchy served as inspiration for the GWO algorithm, which has proven to be highly effective at resolving challenging optimization issues. GWO increases the prediction accuracy and generalization of the GRU model by fine-tuning important hyper parameters including learning rate, hidden layer size, and dropout rate, In comparison to solo models, this optimization step guarantees that the hybrid model obtains greater forecasting skills. [4] We execute comprehensive experiments and compare the performance of our suggested hybrid model with that of standalone Prophet and GRU models, conventional forecasting techniques, and baseline statistical approaches like ARIMA in order to assess its efficacy. To evaluate the accuracy and resilience of the models, we employ common performance metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R2 Score. The comparison study sheds important light on the benefits of hybrid modeling for predicting financial time series. [5]

II. LITERATURE REVIEW

Hyndman et al. [6] demonstrated the efficacy of traditional statistical models like Exponential smoothing and ARIMA in capturing linear trends in time series data. However, these models often fail to account for the non-linear correlations inherent in financial data. To address this limitation, the exploration of machine learning models like Random Forests and Support Vector Machines (SVM) was initiated. Traditional statistical models like ARIMA and Exponential smoothing are effective in modeling linear trends in time series data. However, they struggle with non-linear and complex patterns commonly seen in financial datasets. Choudhary et al. [7] employed SVM and Random Forest to predict crude oil prices and found that these models could outperform traditional time series methods, particularly in terms of prediction accuracy.

However, feature selection to optimize model performance. SVM and Random Forest outperformed traditional models; feature selection is critical. Zhang et al. [8] applied Gated Recurrent Units (GRU) networks to forecast crude oil prices and showed that GRU models outperformed conventional machine learning techniques, such as SVM and Decision Trees, by better capturing the sequential structure of time series data. GRU outperformed SVM and Decision Trees by better modeling sequential dependencies. LI et al [9] utilized Long Short-Term Memory (LSTM) networks for short-term crude oil price forecasting and achieved promising results, demonstrating the effectiveness of LSTM networks in modeling long-term dependencies in sequential data. LSTM achieved high accuracy in short-term forecasting by capturing long-term patterns. Singh et al. [10] proposed hybrid model combining ARIMA and GRU for short-term crude oil price forecasting.

Liang et al. [11] integrated the prophet model with LSTM to improve forecasting accuracy in stock market predictions, showing that the combined model outperformed individual models by effectively capturing both short-term and long-term trends. Prophet-LSTM hybrid improved accuracy by capturing both trend and fluctuations. Zhao et al. [12] proposed a hybrid model combing prophet for long term trend prediction and GRU for residual learning to forecast stock market prices. Their approach demonstrated significant improvements in forecasting accuracy by combining the strengths of both models. Prophet-GRU hybrid significantly enhanced forecasting by combining trend and residual learning. Dong et al. [13] utilized Grey Wolf Optimization (GWO) to optimize the hyper parameters of machine learning and deep learning models for crude oil price forecasting. Their results showed that GWO optimization improved the performance of hybrid models by fine-tuning their parameters, leading to enhanced forecasting accuracy. GWO optimization improved model accuracy by fine-tuning hyper parameters.

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Zhu et al. [14] focused on integrating LSTM and GRU to predict the volatility of crude oil prices, which is a crucial aspect of financial forecasting. Their hybrid model showed robust results, outperforming traditional models by capturing both short-term trends and long-term dependencies. LSTM-GRU hybrid effectively predicted volatility, outperforming traditional methods. Wang et al. [15] proposed a hybrid deep learning model combining Convolutional Neural Networks (CNN) and LSTM for forecasting crude oil prices.

III. METHODOLOGIES

Overview of the Methodology

This study proposes a hybrid machine learning method that combines deep learning and conventional statistical models to estimate crude oil prices. In particular, we suggest a hybrid model that combines the Gated Recurrent Unit (GRU) model for short-term fluctuation prediction with the Prophet model for long-term trend forecasting. Furthermore, in order to improve performance, we adjust the hyper parameters of the GRU model using Grey Wolf Optimization (GWO). The technique is organized as follows:

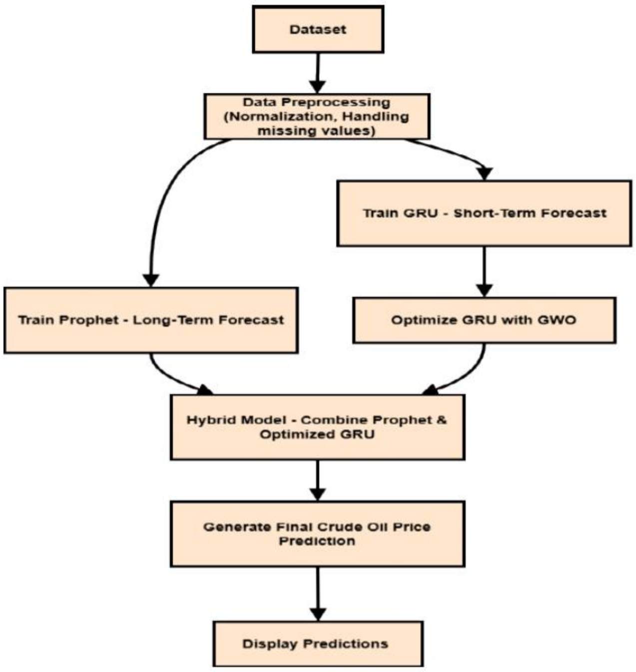

Fig 1: system Architecture

Dataset Collection:

We make use of Crude Oil Price Dataset, which contains historical data on crude oil prices as well as other market variables. It has the following characteristics:

The target variable is the price of crude oil. The goal variable that we are trying to forecast is (Close/Last).

Feature that Explain:-

Volume: The amount of crude oil that is exchanged.

Open: Crude oil's opening price for the day.

High: The day's highest crude oil price.

Low: the day's lowest crude oil price.

1. Preprocessing data and conducting Exploratory Data Analysis (EDA):

Historical crude oil prices with characteristics like Open, High, Low, Close, and Volume make up the dataset used in this investigation. Loading the dataset and doing exploratory data analysis (EDA) to comprehend its properties constitute the initial and handle missing values. To make time-series analysis easier, the Date column is transformed into a date time format and assigned as the index. To maintain sequential integrity, the dataset is arranged chronologically. To improve numerical stability during training, normalization is applied using Min Max Scaler which scales all feature values between 0 and 1. After that, the dataset is divided into subsets for testing and training, with 20% set aside for assessment and the remaining 80% used for training. Time-series sequences are created using a sliding window technique, with each sequence consisting of ten consecutive data points that are used to forecast the series future value. Models can learn sequential patterns in crude oil prices because to this method, which incorporates temporal interdependence. Line plots showing crude oil prices over time are one example of a visualization that sheds light on both short-term volatility and long-term trends.

2. Forecasting Long-Term Trends with Prophet:

The Prophet model, created by Facebook, is used in the first forecasting method to identify long-term patterns in crude oil prices. Prophet integrates trend, seasonality and holiday impacts into its additive time-series decomposition methodology. The dataset is structured in accordance with prophet's input specifications before to training, changing the Close/Last column to y and the Date column to ds. The model is trained using the historical data and is set up with an annual seasonality component.

Using an additive time-series decomposition methodology, Prophet predicts the price of crude oil as follows:

$$y(t) = g(t) + s(t) + h(t) + Et \text{ ---------------------------------} \rightarrow (1)$$

Where:

g(t)- Trend

s(t)- Seasonality

h(t)- Event/Holiday impacts

Et- The error term

The Prophet model produces forecasts for the testing period following training. The prediction provides a range of possible outcomes by including the upper and lower confidence intervals in addition to the projected values(yhat). Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R2 Score are used to analyze Prophet's performance and determine how well it captures long-term price trends. Prophet's dependence on additive components makes it difficult to handle short-term fluctuations, even though it is a good model for long-term movements. This makes the incorporation of a more dynamic short-term forecasting model necessary.

3. GRU-Based Short-Term Forecasting:

Using a Gated Recurrent Unit (GRU) model, short-term price variations are captured. Recurrent Neural Networks (RNNs), of which GRUs are a kind, are made to effectively process sequential data. Two stacked GRU layers and dropout layers are used in the design of the GRU model to avoid over fitting. The final output layer, which predicts the subsequent price in the sequence, is a dense layer with the activation function ReLU. The loss function's Mean Squared Error (MSE) is minimized using the Adam Optimizer. Normalized time-series sequences of length 60 are fed into the model throughout the training process. Each sequence contains historical observations that are used to forecast the subsequent value. MAE, RMSE and R2 size of 32. Although the GRU model does a good job of capturing short-term dependencies, its effectiveness is dependent on the choice of hyper parameters, which is then optimized using Grey Wolf Optimizer (GWO) in the following phase.

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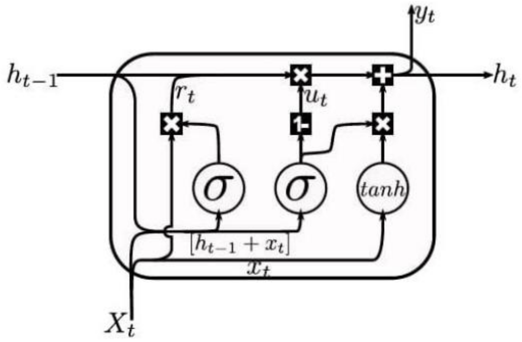

Fig 2: GRU Architecture Block Diagram

4. Grey Wolf Optimizer (GWO) optimization of GRU

For hyper parameter optimization, the Grey Wolf Optimizer (GWO) is used to increase the predictive accuracy of the GRU model. GWO is a met heuristic optimization inspired by nature that imitates the hunting strategy and leadership structure of grey wolves, minimizing the RMSE of the GRU model is the definition of the optimization objective function. Important hyper parameters are included in the optimization search space:

There are 32, 64, and 128 GRU units.

The percentage of dropouts (0.1,0.2,0.3,0.4)

The rate of acquisition (0.001,0.005,0.01)

The size of the batch (16,32,64)

The ideal set that produces the lowest RMSE is chosen by the GWO algorithm, which iteratively investigates various combinations of the hyper parameters. Following the identification of the optimal hyper parameters, the optimized GRU model is retrained with these settings and assessed on the test set. It is anticipated that the optimized model will perform better in terms of prediction stability and accuracy than the baseline GRU model.

5. Hybrid Forecasting Integration Module and Evaluation

To capitalize on their complementary qualities, Prophet and the refined GRU model are integrated into the final forecasting model. Short-term residual changes are modeled by the GRU model, which is optimized using GWO, whereas Prophet successfully catches long-term trends. The steps in the hybrid approach are as follows: Long-Term Trend Extraction from Prophet: It extracts the trend component (y_trend) from the prophet model's prediction.

The underlying long-term movement of crude oil prices is shown by this. Residual Calculation: Subtracting the long-term trend from the actual prices yields the residuals (y_residual). Prophet is unable to catch the short-term oscillations that are represented by these residuals. Educating Prediction Calculation: using the same time-series sequence method, a second GRU model is trained with the residual values as a new target variable. Around the long-term trend, this GRU model learns a forecast short-term fluctuations.

Final Prediction Calculation: The final crude oil price forecast is calculated by adding the projected residuals (y_residual_pred) from the GRU model and the trend forecast (y_trend) from the prophet model. This hybrid strategy guarantees that the model accurately depicts both short-term and long -term price fluctuations.Assessment and

Analysis of Performance

The performance of the suggested hybrid model is thoroughly assessed in comparison to the solo Prophet and GRU models. MAE, RMSE, R2 Score is measured.

Mean Absolute Error (MAE): The average absolute difference between actual and predicted values.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |\mathrm{yi} - \bar{\mathrm{yi}}| \qquad (2)$$

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Root Mean Squared Error (RMSE): RMSE measures the square root of the average squared differences between actual and predicted values.

$$\text{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(yi-\bar{y}i)^2} \quad (3)$$

R^2 Score: The R2 Score represents the proportion of variance in the actual values that is explained by the models. It tells how well the model fits the data.

$$R^2 = 1-\frac{\sum_{i=1}^{n}(yi-\bar{y}i)^2}{\sum_{i=1}^{n}(yi-\bar{y})^2} \quad (4)$$

IV. RESULT AND ANALYSIS

Performance Comparison:

The forecasting performance is interpreted through visual analysis. Price trends for Prophet, GRU, and the hybrid model compared to actual. Residual graphs that displays the GRU-captured short-term variations. Graphs of trend-residual decomposition to show how the hybrid model combines the two elements. By using Prophet for long-term trends and GWO-optimized GRU for short-term variations, the suggested hybrid model greatly enhance crude oil price predictions. Compared to solo models, the hybrid technique provides higher accuracy and reduced error rates, indicating its durability in time-series forecasting.

Model	MAE	RMSE	R2 Score
Prophet	0.684	1.005	0.997
Optimized GRU (GRU)	0.012	0.016	0.976
Hybrid Model	0.011	0.018	0.982

- This figure illustrates the historical price changes of crude oil from 2012 to 2023, emphasizing significant market crashes and patterns.

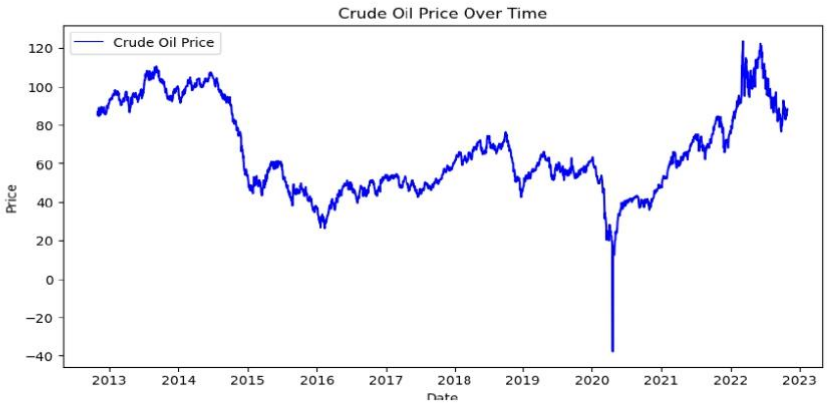

Fig 1: Cude Oil Prices Over Time

- This graph shows a close match in trend and seasonality between actual and prophet model forecasts for crude oil prices.

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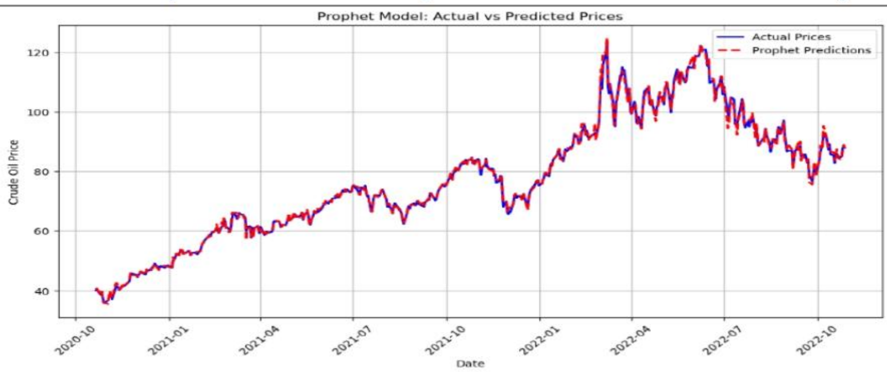

Fig 2: Prophet Model Prediction

- This graph illustrates the practically flawless tracking of the optimized GRU model in predicting normalized sine-wave- like data

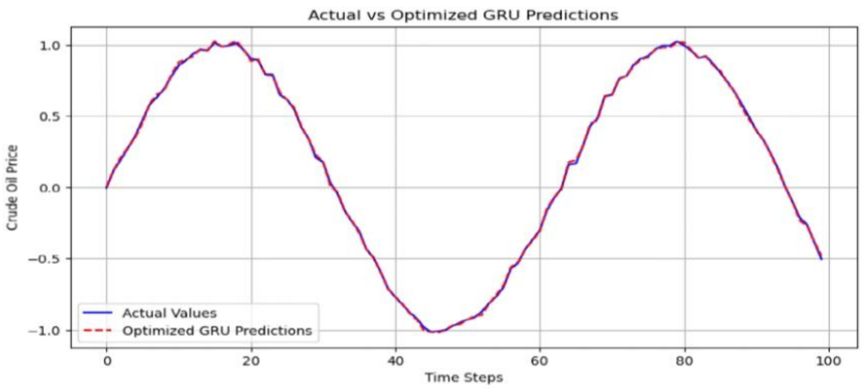

Fig 3: Optimized GRU Prediction

Fig 4: Hybrid Model (long term + short term) prediction

- This graphs shows better alignment than the standalone models by comparing real crude oil prices with forecasts from a weighted hybrid model that combines prophet and GRU.

V. CONCLUSION

In order to increase the accuracy of crude oil price forecasting, this work propose a hybrid forecasting model that combines Prophet for long-term trend estimation with Grey Wolf Optimizer (GWO) tuned GRU for short-term volatility prediction. The suggested method outperforms stand-alone models in terms of prediction by utilizing prophet capacity to identify patterns and seasonality in conjunction with an improved GRU model that efficiently learns short-term dependencies. According to experimental results, the hybrid model improves overall accuracy by including both long-term trend and short-term fluctuations and obtaining lower MAE, RMSE with a higher R2 score. By lowering overfitting and guaranteeing improved hyperparameter selection, the incorporation of GWO optimization greatly enhances GRU performance. The results indicate that a more robust and dependable approach to financial time-series forecasting can be achieved by combining statistical forecasting approaches with deep learning models and metaheuristic optimization methods. The energy markets, risk management, and financial decision-making are all significantly impacted by this hybrid method, which provides a potent instrument for more accurate crude oil prediction. To improve forecast accuracy even more, future studies can investigate different optimization strategies and other external elements like macroeconomic data and geopolitical events.

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*This is to certify that author "**C Preethi**" with paper ID "**IRJMETS70400085425**" has published a paper entitled "CRUDE OIL PRICE HYBRID FORECASTING USING PROPHET AND GRU"* ***in International Research Journal Of Modernization In Engineering Technology And Science (IRJMETS), Volume 07, Issue 04, April 2025***

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