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Deep Learning Approaches in the Effects of Recession and FOMC Minutes on Oil Prices

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ABSTRACT: The financial industry is increasingly interested in predictive analysis and forecasting using time series data. Understanding the relationship between recessions and oil markets is crucial for developing financial forecasts and strategic decisions. This study uses advanced deep learning models to examine the interaction between recession signals and crude oil prices. Data covering recession periods include key economic indicators such as Gross Domestic Product (GDP) fluctuations, unemployment rates, consumer spending trends, business investments, and housing market dynamics. Additionally, Federal Open Market Committee (FOMC) minutes are used to capture economic assessments and monetary policy decisions by the Federal Reserve during recessions, providing insights into policymakers' expectations and responses. Data is augmented using Time-series Generative Adversarial Networks (TimeGAN) to capture intricate patterns in oil prices. By focusing on feature selection, this study aims to identify patterns from historical data and relationships between recession signals and oil price movements. Long Short-Term Memory networks(LSTMs), GatedRecurrentUnits(GRUs), Transformer, and ensemble learning techniques are used to predict crude oil prices during recessions.

I. INTRODUCTION

The financial industry increasingly relies on predictive analysis of time series data, with recession–oil market dynamics being critical for forecasts and strategic decisions. This study applies advanced deep learning models—LSTMs, GRUs, Transformers, and ensemble methods—alongside TimeGAN-augmented data to capture complex oil price patterns during recessions. Inputs include GDP fluctuations, unemployment, consumer spending, investments, housing trends, and FOMC minutes that reflect monetary policy responses. Through feature selection and multimodal analysis, the research highlights how recession signals and Federal Reserve decisions influence crude oil prices, offering a comprehensive view of energy market behavior in economic downturns.

II. LITERATURE SURVEY

Title: Predicting stock market index using LSTM

Author: Hum Nath Bhandari, Binod Rimal, Nawal Raj Pokhrel, Ramchandra Rimal, Keshab R. Dahal, Rajendra K.C. Khatri

Year: 2022

Description : This study uses a long short-term memory (LSTM), a particular neural network architecture, to predict the next-day closing price of the S&P 500 index.

Title: The Power of Text-based Indicators in Forecasting the Italian Economic Activity(2023)**Author:** Valentina Aprigliano, Simone Emiliozzi, Gabriele Guaitoli, Andrea Luciani, Juri Marcucci, Libero Monteforte

Year: 2023.

Description : We develop high-frequency text-based indicators (TESI and TEPU) to measure sentiment and policy uncertainty across the economy. Using Bayesian Model Averaging, these indicators improve short-term macroeconomic forecasts, especially during recessions

Title: Real-time Visual Inspection System for Grading Fruits using Computer Vision and Deep Learning Techniques

Author: Sahar Erfanian, Yewang Zhou, Amar Razzaq

Year: 2024

Description: This study predicts Bitcoin (BTC) prices using machine learning and economic theories, addressing limitations of purely empirical research. It compares models like OLS, Ensemble, SVR, and MLP, finding SVR performs best, with technical indicators useful short-term and macro/blockchain factors long-term.

Title: A comprehensive review on ensemble deep learning:
Opportunities and challenges

Author: Ammar Mohammed, Rania Kora

Year: 2025

Description : It explains different ensemble strategies, factors affecting their success, and challenges like complex hyperparameter tuning. The study highlights current methods, their limitations, and applications of ensemble deep learning across various domains.

III. EXISTING SYSTEM

Existing System:

Traditional models like ARIMA and VAR rely on historical economic data but struggle to capture complex nonlinear relationships and sudden market changes during recessions.

They often exclude qualitative factors, such as Federal Reserve assessments, which limits predictive accuracy.

They are inefficient at handling large-scale unstructured data, resulting in less robust forecasts during volatile periods.

Disadvantages:

- Limited ability to capture non-linear relationships
- Reliance on stationarity assumptions
- Inability to incorporate qualitative policy data

IV. PROPOSED SYSTEM

Uses advanced deep learning models (LSTM, GRU, Transformers, ensemble learning) to capture complex relationships and improve oil price forecasting during recessions. Adapts to changing market trends through sequential learning and enhances data using TimeGAN for better generalization. Incorporates textual analysis of FOMC minutes, combining economic indicators with policy insights for more accurate predictions.

ADVANTAGES

- Superior modeling of complex, non-linear relationships
- Enhanced processing of multi-dimensional datasets with deep learning
- Integration of qualitative data (e.g., FOMC minutes)
- Robust performance during periods of market volatility

V. SYSTEM ARCHITECTURE

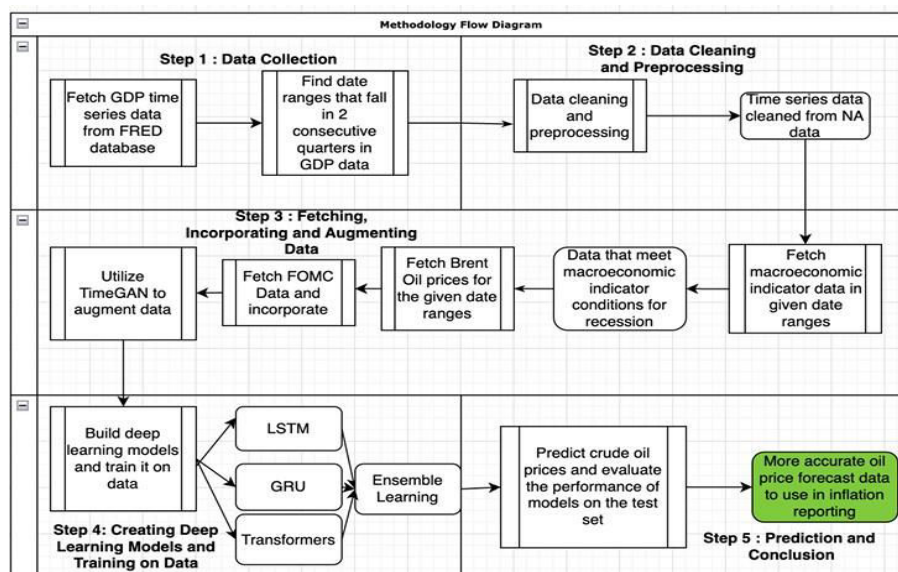


Fig 1: System Architecture

The System Architecture illustrates a structured workflow for forecasting crude oil prices using deep learning. It begins with data collection from GDP and other economic sources, followed by cleaning and preprocessing to ensure accuracy. Next, diverse datasets such as FOMC reports, Brent oil prices, and macroeconomic indicators are fetched and augmented with TimeGAN. Advanced models like LSTM, GRU, Transformers, and ensemble methods are then trained on this prepared data. Finally, the system performs prediction and evaluation, delivering reliable oil price forecasts that aid in economic and inflation reporting.

VI. METHODOLOGIES

MODULES NAME:

1. Extracting Data
2. Making Sense of Data
3. Structuring Information
4. Operating the model
5. Correcting Deviations

Modules Explanation:

1. Extracting Data:

The study collects historical economic data, including recession indicators such as GDP fluctuations, unemployment rates, consumer spending trends, and business investments. Additionally, it incorporates crude oil price movements and Federal Open Market Committee (FOMC) minutes. These datasets provide a comprehensive foundation for understanding the interaction between economic downturns and oil markets. The data is sourced from reliable financial institutions and government reports to ensure accuracy.

2. Making Sense of Data:

To understand the relationship between recessions and oil prices, the study applies exploratory data analysis (EDA). Trends, correlations, and anomalies are identified within the dataset to gain deeper insights. Feature selection techniques help in extracting the most relevant economic indicators for analysis. The goal is to highlight key recession signals that impact crude oil price fluctuations.

3. Structuring Information:

The dataset is preprocessed by handling missing values, normalizing numerical variables, and encoding categorical information where necessary. Time-series data is structured in a way that captures historical trends and dependencies. Feature engineering techniques help refine the dataset for better predictive accuracy. Proper structuring ensures that the deep learning models can effectively learn complex patterns.

4. Operating the Model:

The study employs advanced deep learning models, including Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), Transformers, and ensemble learning methods. These models analyze time-series data to predict oil price movements during recessions. The integration of Time-Series Generative Adversarial Networks (TimeGAN) enhances data augmentation and model training. The models are trained using optimized hyperparameters to improve forecasting precision.

5. Correcting Deviations:

Performance evaluation is conducted using metrics like Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Any deviations in predictions are addressed by fine-tuning the models and adjusting learning rates. Regularization techniques help prevent overfitting and ensure generalization. Cross-validation methods are applied to enhance model robustness.

VII. ALGORITHM USED

EXISTING TECHNIQUE: -

ARIMA is a widely used statistical forecasting algorithm for time series analysis. It combines autoregression (AR), differencing (I), and moving average (MA) components to model time-dependent relationships in financial data. The AR component predicts future values based on past observations, the I component stabilizes the series by removing trends, and the MA component accounts for past forecast errors to improve accuracy. However, ARIMA is limited in capturing complex nonlinear relationships in financial markets, especially during economic downturns. It assumes

stationarity, meaning the underlying statistical properties of the data remain constant over time, which is often not the case in highly volatile markets like crude oil. Additionally, ARIMA struggles with high-dimensional, multi-variable datasets, making it less effective for modeling economic indicators alongside oil price movements.

PROPOSED TECHNIQUE USED: -

LSTM is a type of recurrent neural network (RNN) designed to address the vanishing gradient problem in sequential data modeling. It introduces memory cells with input, forget, and output gates that regulate the flow of information over time, allowing the model to retain long-term dependencies. This makes LSTM particularly effective for financial forecasting, where past economic trends influence future market behavior. In the proposed system, LSTMs are used to analyze historical oil prices and recession signals, learning complex dependencies that traditional models fail to capture. By incorporating additional deep learning techniques such as GRUs and Transformers, the system enhances predictive performance. The integration of TimeGAN further enriches the dataset, ensuring the model learns from a more diverse range of economic scenarios. This combination results in a robust forecasting framework capable of predicting oil price fluctuations with high accuracy during recession.

VIII. EXPERIMENTAL RESULTS

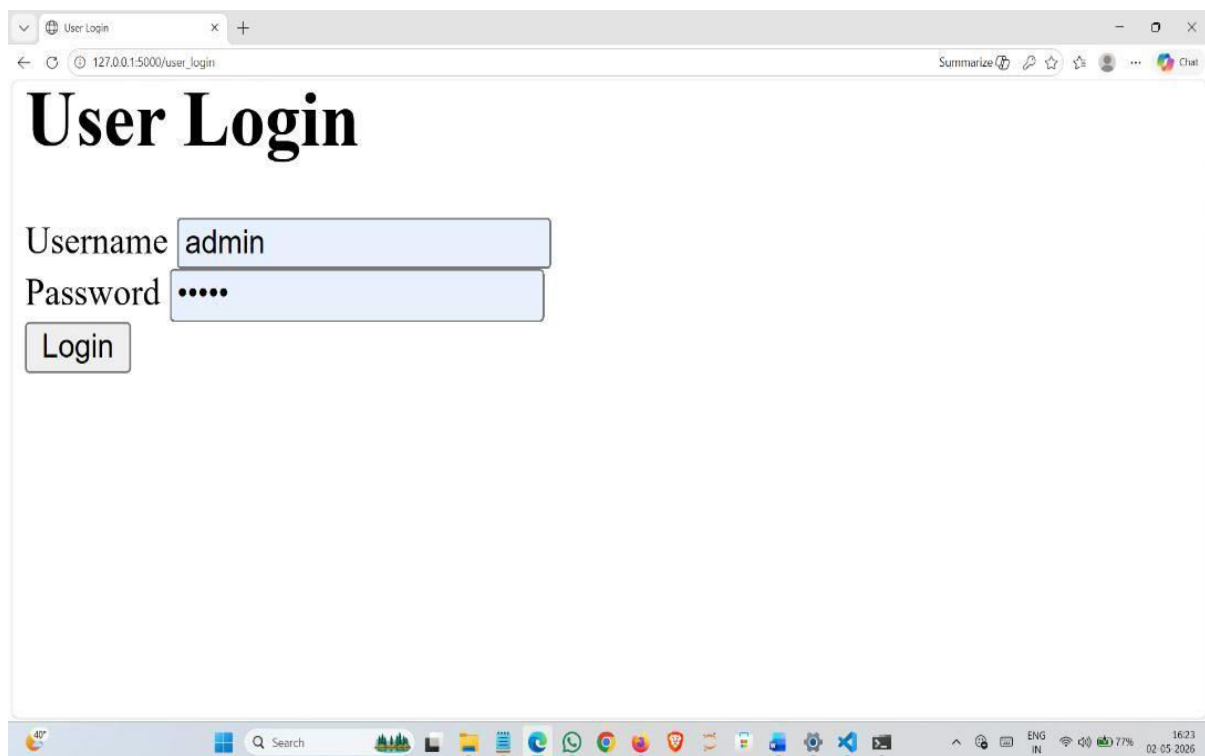


Fig 1: LOGIN PAGE

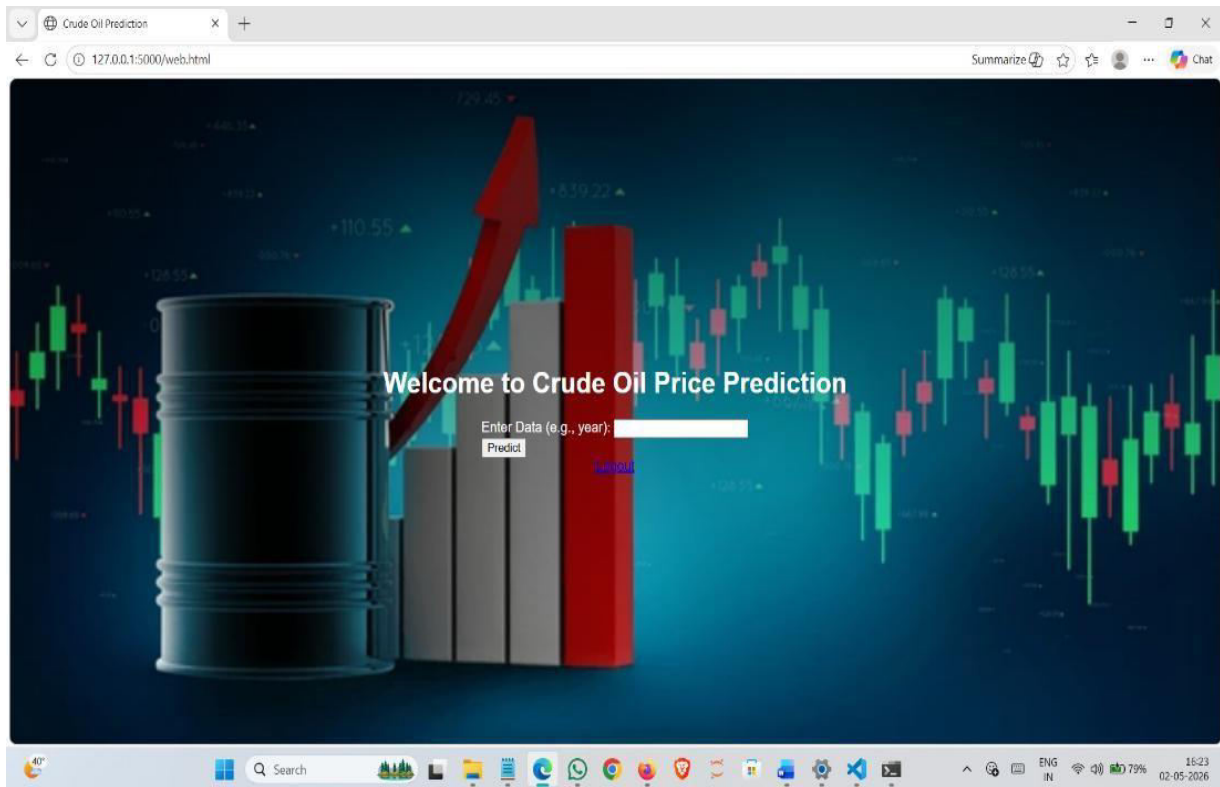


Fig 2: PREDICTION INTERFACE

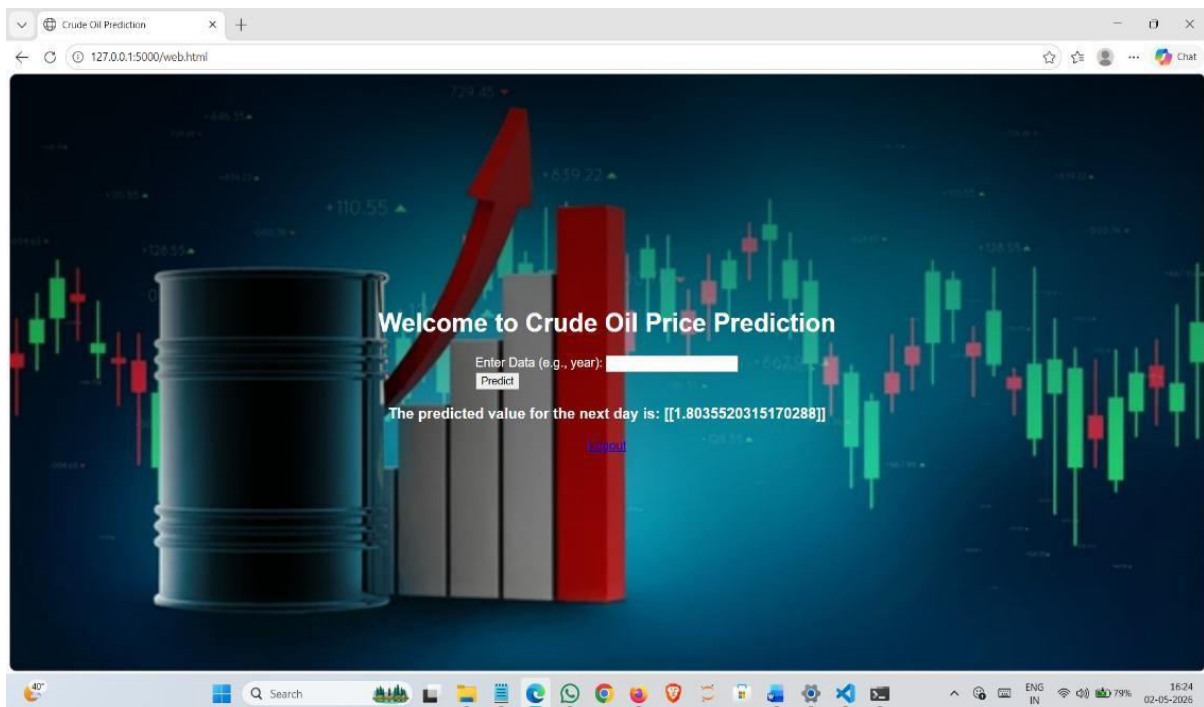


Fig 3: RESULT PAGE

IX. CONCLUSION

This study provides a comprehensive analysis of the relationship between economic recessions and crude oil prices using advanced deep learning models. By incorporating key recession indicators, Federal Reserve policy decisions, and enhanced time-series data augmentation techniques, the research effectively captures complex market dynamics. The proposed approach improves forecasting accuracy, offering valuable insights for financial analysts, policymakers, and energy market stakeholders.

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