International Journal of Engineering and Science Invention (IJESI)
ISSN (Online): 2319-6734, ISSN (Print): 2319-6726
www.ijesi.org ||Volume 15 Issue 6 June 2026 || PP 01-09

Genaretive AI For Financial Time Series Forecasting a Case Study on Crudeoil

Vinod[1],MeghaRaniRaigonda[2]

[1] *Vinod,DepartmentofComputerScienceandEngineering(MCA),VisvesvarayaTechnologicaluniversity,CPGS,Kalaburgi ,Karanataka, India*

[2] *MeghaRaniRaigonda,DepartmentofComputerScienceandEngineering(MCA),VisvesvarayaTechnologicalUniversity, CPGS, Kalaburgi, Karnataka, India*

Abstract: *Crude oil price fluctuations significantly affect the global economy, but traditional forecasting models such as (ARIMA) Autoregressive IntegratedMoving Average and (GARCH) Generalized Autoregressive Conditional Heteroskedasticity strugglewiththenonlinearandunstabledynamicsof thesemarkets.Advances indeeplearning,including LSTM Long Short-Term Memory and Transformer architectures, have improved predictions but remain limited by data scarcity and unexpecteddisruptions. Toaddresstheseissues,this work develops a hybrid framework that integrates LSTM for short-term sequence learning, Transformersforcapturinglong- range patterns using attention, and TimeGAN for generating synthetic time-series data to strengthen modeltraining.Usinghistoricaldatasetsfromthe U.S. Energy Information Administration (EIA), the system is assessed with error measures such as RMSERootMeanSquaredError,andMAPEstands forMeanAbsolutePercentageErrorResultsindicate that this combined approach achieves more reliable and accurate forecasts than standalone models, highlighting the value of combining predictive and generative AI for robust commodity price forecasting.*

Keywords*: This work emphasizes hybrid AI frameworks for forecasting crude oil prices by combining sequence-learning models with generative approaches. Important keywords include generative AI, TimeGAN, commodity price volatility, long-range dependency modeling, and robust predictive performance*

Date of Submission: 26-05-2026 Date of acceptance: 05-06-2026

I.INTRODUCTION

This project is implemented in Python using a modular and well-structured architecture, ensuring clarity, flexibility, and long-term scalability. The framework integrates traditional statistical forecasting techniques, advanced deep learning architectures, and generative AI models to build a comprehensive solution for crude oil priceprediction.BycombiningLSTMnetworksforshort-termtemporallearning,Transformermodelsforcapturing long-range dependencies, and TimeGAN for generating high-quality synthetic time-series data, the system effectivelyhandlesthenonlinear,volatile,anddata-scarce nature of commodity markets.

Each stage of the workflow—data collection, preprocessing, feature engineering, model training, performance evaluation, and visualization—is implementedasanindependentPythonmodule.This separation enhances code reusability, simplifies debugging, and allows updates or model improvements without affecting the entire pipeline. The use of historical datasets from reliable sources enables realistic forecasting, while metrics such as RMSEandMAPEprovideanobjectiveevaluationof predictive accuracy. Overall, this modular hybrid framework serves as a robust and scalable approach for financial time series forecasting, especially in unstable market environments like crude oil.

II.LITERATURESURVEY

TheSurveystudiesshowthattraditionalmodelslike ARIMA struggle with the nonlinear and volatile nature of crude oil prices. Deep learning methods such as LSTM, CNN-LSTM, and Transformers provide better accuracy by capturing complex temporal patterns. TimeGAN further enhances performancebygeneratingsyntheticdatatoimprove model robustness.

[1] Vapnik (1995) – SVM / SVRVapnik introduced SupportVectorMachines(SVM)andSupportVector Regression (SVR), which model nonlinear relationshipsusingkernelfunctionssuchasRBFand Polynomial. SVR is effective in small and medium datasets because it finds a globally optimal solution andavoidsoverfittingthroughmarginmaximization. It can capture nonlinear price patterns but relies heavily on careful tuning of kernel type and parameters.However,SVRdoesnotnaturallymodellong sequential dependencies unless windowed inputs are engineered manually. For crude oil forecasting, SVR performs well for short-term prediction but struggles with long temporal dynamics

[2].Breiman (2001) –Random ForestsBreiman proposed Random Forests, an ensemble of decision trees trained using bootstrap samplingandrandomfeatureselection.Thismethod reduces overfitting, handles noisy inputs, and manages nonlinear feature interactions effectively. Random Forests can process complex financial datasets without strong assumptions about their distribution. However, they do not inherently capturesequentialortemporaldependenciesunless lagfeaturesaremanuallycreated.Thus,theirutility in crude oil forecasting is limited to short-term or feature-based prediction tasks rather than long- horizon forecasting.

[3]. Hochreiter &SchmidhuberLSTM LSTM networkswereintroducedtosolvethevanishingand exploding gradient problems recurrent Neural networksbyincorporatinggatedmemorycells.Theycan Store Long Term dependencies and learn temporal patternsinhighlyvolatiletimeseriesdatasuchascrude oil prices. LSTM have strong performance in sequence

[4].Huetal.(2021)–CEEMDAN-LSTM Hybrid Hu et al. developed a hybrid model combining CEEMDAN decomposition with LSTM networks. CEEMDAN breaks the crude oil price series into multiple intrinsic mode functions (IMFs), effectively separating trends, cycles, and noise. Each component is learnedusinganLSTM,andpredictionsarerecombined to obtain the final output. This approach enhances forecasting accuracy by reducing data complexity and isolatingmulti-scalepatterns.Themajordrawbackisincreased computational cost and longer training times due to multiple models. It is particularly suited for nonstationaryandvolatilecrudeoilpricedata

[5].Yoon et al. (2019) – TimeGANTimeGAN is a generative adversarialmodel designedspecificallyfortimeseries, integrating embedding networks, supervised learning, andadversarialtraining.Itgeneratesrealisticsyntheticsequenceswhilepreservingtemporalrelationsand featuredependencies.TimeGANisvaluableforcrudeoil forecastingbecauseitcanaugmentdatasets,simulate rare events, and support model training with more diversepatterns.However,GANsareoftenunstable to train and may suffer from mode collapse if nottunedproperly.Despitethesechallenges,TimeGANisaninfluentialmodelin timeseries augmentation.

[6].Heetal.(2023)–Temporal FusionTransformer(TFT)Heetal.appliedthe TemporalFusionTransformer(TFT)tocrudeoil forecasting,showingsignificantimprovementsover LSTMinmedium-andlong-termhorizons.TFT combinesLSTMlayerswithattentionmechanisms,variableselectionnetworks,andgatingmodules,enablingittocapture long-rangedependenciesand heterogeneousfeatureinteractions.Itsinterpretability allowsuserstoidentifyimportantvariablesandtime windows influencingforecasts.Although computationallyintensive,TFToffersstate-of-the-art accuracyinmulti-horizonforecastingtasks.Itisespecially effectivefordatasetswith many macroeconomicandtemporal features.

[7].Hamilton(2009)–EconometricAnalysisof OilShocksHamilton’s workdemonstratedthatcrudeoil prices are heavily influenced by external shocks such as geopoliticalevents,supplydisruptions,andmacroeconomicuncertainty.UsingeconometricmodelslikeVARandstructural decomposition,heshowedthatmanysuddenpricechanges are not predictable from historical data alone. Thischallengespurelydata-drivenmodelsandhighlights theneedtoincludeexogenous variables.While valuable forunderstandingmarketmechanisms,thesemodels oftenfailduringperiodsofextremevolatility. Hamilton’sfindingsemphasizetheimportance of shock modelinginoilforecastingresearch.

[8].Zhangetal. (2018) – ARIMA-LSTM Hybrid Zhanget al. developed ahybridforecasting.methodcombiningARIMAfor linearcomponentsandLSTMfornonlinearresiduals. ARIMA captures autoregressive and seasonal behavior, whileLSTMmodelscomplexnonlineardynamicsleft unexplainedbythestatisticalmodel.Thistwo-stage system effectively reduces forecasting error, especially duringvolatilemarketperiods.Themethodissimpleand interpretable but requires correct ARIMA specification andcarefulresidualmodeling.Itiswell-suitedforcrude oildatawherelinearandnonlinearpatternscoexist.

[9].Qinetal.(2017)–DA-RNN(Dual-Stage AttentionRNN)DA-RNNintroducestwoattention mechanisms: input attention to select important features andtemporalattentiontoassignweightstopasttimesteps. This structure improves interpretability and focusesthemodelonrelevantsignalsinmultivariatetime series. It outperforms traditional RNNs in forecasting tasks by reducing noise influence and dynamically adjusting attentionduring training. However, it still retains the limitations of RNNs, such as slower training andsomedifficultyinhandlingverylongsequences.DA- RNNiseffectiveforcrudeoilforecastingwhen multiple economicindicatorsareincluded.

[10].Chenetal.(2020)– CNN-LSTMHybridChenetal.proposedahybridCNN- LSTM model that first uses convolutional layers to extract local temporal patterns and then uses LSTMs to capturelong-termdependencies.Thisapproach is highly effective for high-frequency or noisy financial data because CNNs detect short-term features like spikes or microstructure patterns. The combination enhances forecasting accuracy compared to standalone LSTMs. However, the model requires careful design of convolutionalwindowsizesandmayoverfitwithlimited data. It is especially useful for intraday crude oil forecasting.

III.PROPOSEDMETHODOLOGY

This study aims to close this gap by combining LSTM, Transformer, and TimeGAN models, showing that their integration can deliver more precise and robust results.Crude oil is a vital global resource, and price fluctuations have direct consequences on financial markets, inflation, and economicstability.Marketvolatilityisinfluencedby factors such as geopolitical conflicts, OPEC decisions, supply–demand imbalances, currency fluctuations, naturaldisasters, and speculation. Even minor price shifts can significantly affect industries like energy, manufacturing, and transportation. Therefore, accurate forecasting is critical for governments, businesses, and investors to manage risks.Traditional models such as ARIMA, GARCH, and regression approaches were widely applied, but they fail to address nonlinear dynamics, long-term dependencies,andsuddenshocks.Neuralmodelslike RNNsand LSTMs improved sequential learning but require large datasets and struggle with very long input sequences. More recently, Transformer architecturesand TimeGANhave shownpromise by handling long-term dependencies and generating synthetic sequences, yet their use in crude oil forecasting remains relatively unexplored.

- DataCollection&Preprocessing**:**Gathercrude oil prices from reliable financial platforms, clean and normalize the dataset, and derive technical indicators.
- BaselineModels:DevelopARIMAandasimpleLSTMas benchmarks.
- Transformer Forecasting :Design a Transformer model to capture nonlinear long- range patterns.Synthetic Data Generation: Applying TimeGAN to create realisticsynthetic datasets for robustness and augmentation.
- Performance Evaluation: Compare models using MAE, RMSE, MAPE, and R^2.
- Visualization & Interpretation: Present results through charts, dashboards, and tables for clear analysis.
- Comparative Analysis: Identify the most effective model under volatile market scenarios.
- Practical Contribution: Demonstrate how generativeAIcanenhancereliabilityandaccuracy in crude oil price prediction.

The methodology follows a modular pipeline beginning with data collection and preprocessing, where historical crude oil prices are cleaned, normalized, and transformed for model readiness. LSTM and Transformer models are then trained to learn short-term and long-term patterns, while TimeGAN generates synthetic time-series data to enhance training. Finally, model predictions are evaluated using metrics like RMSE and MAPE to ensure accurate and reliable forecasting.

Step 1-Literature Review & Problem Definition: Analyze existing models such as ARIMA, GARCH, and LSTM, identify their limitations, and justify the use of generative AI (Transformers, TimeGAN).

Step 2-Data Collection: Obtain crude oil price data (WTI and Brent) from Yahoo Finance, FRED, and Kaggle, including daily closing prices and trading volumes.

Step 3-Preprocessing: Handle missing values and outliers,normalizeusingmin–maxscaling,andcreate features like moving averages, volatility, and momentum indicators.

Step 4-Model Development: Implement ARIMA (baseline), LSTM (sequential learning), Transformer (long-range dependency), and TimeGAN (synthetic data generation).

Step 5-Training: Train models with optimized hyperparameters (batch size, learning rate, dropout) and apply techniques like regularization and early stopping.

Step 6-Evaluation: Assess performance using MAE, RMSE, MAPE, and R^2 on test datasets.

Step7-Visualization&Analysis: Compareactualvs. predicted prices with visual dashboards, error plots, and volatility analysis.

Step 8-Results & Conclusion: Determine the most effectivemodel,highlighthowgenerativeAIenhances prediction robustness, and discuss its practical use in finance and energy domains.

System takes a fundamental stage of software development since it defines the architecture and structural framework of the proposed solution. In this project,thedesign illustrateshowdatamoves fromits initial collection and preprocessing stages, through model development, and finally to the generation of forecasts. It clearly specifies the components of the system, howtheyinteract, and how information flows between them. The architecture follows a modular approach, meaning each part of the system has a specific role and can be updated or replaced independentlywithoutaffecting theoverallworkflow. The key architectural layers consist

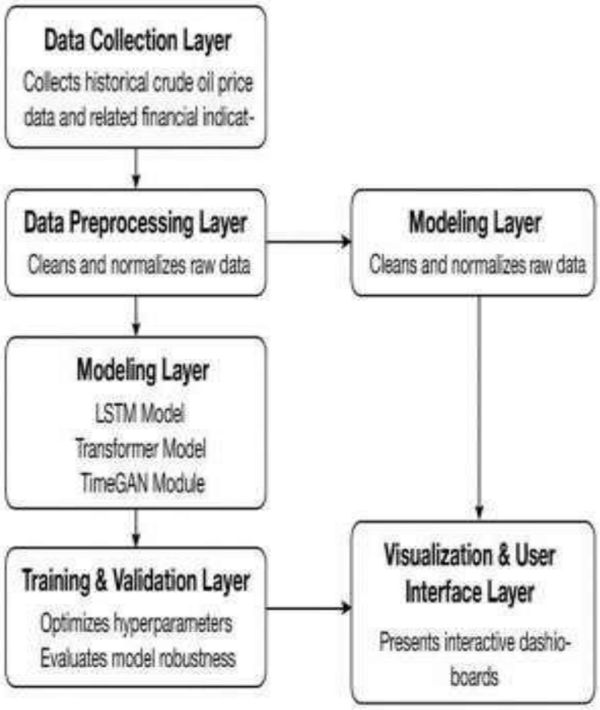

Figure1:System Architecture

The architecture is designed to be modular and scalable,makingitadaptabletoevolvingdatasetsand methodologies. Beyond generating forecasts, the frameworksupportstheevaluationandcomparisonof multiple models, enabling more informed, data- driveninsights**.**TheGenerativeAIforCrudeOilPrice Forecasting system functions as an intelligent decision- support platform. It collects and refines historicalpricedata,processesitthroughadvancedAI methods, and generates forecasts supported by interactive visualizations. The entire workflow operatesasadata-drivenpipelinethatbeginswithraw input and ends with actionable predictive insights

DataCollectionLayer

- Collects historical crude oil price data from reliable public sources such as financial APIs, governmentdatabases,andmarketrepositories.
- Gathers additional macroeconomic indicators (e.g., exchange rates, stock indices, economic signals) to enrich model inputs.
- Ensures continuous and automated data retrieval for up-to-date forecasting.
- Performsinitialvalidationtoremovemissingor corrupted records.

DataPreprocessingLayer

- Cleans raw data by handling missing values, correcting anomalies, and removing outliers.
- Normalizes numeric variables using Min–Max or Z-Score scaling to ensure uniform model input.
- Constructssupervisedlearningsequencesusing sliding window approaches.
- Generates technical indicators (moving averages, volatility, etc.) to improve model learning quality.
- Outputsawell-structureddatasetreadyfordeep learning and generative modeling.

ModelingLayer

- **LSTMModel:**Capturesshort-andlong-term temporal dependencies in crude oil price movements**.**
- **TransformerModel**:Leveragesself- attention mechanisms to detect long-rangerelationshipsandmarkettrends.
- **TimeGANModule:**Synthesizesrealistic time-series data to augment training datasets and improve

generalization

Training&ValidationLayer

- Trains models using optimized hyperparameters (learning rate, batch size, epochs, layers).
- Uses real and synthetic datasets to evaluate robustness and check for overfitting.
- Applies validation metrics (MAE, RMSE, MAPE, R^2) for accurate performance assessment.
- Performsearlystoppingandcheckpointingfor stable model convergence.
- Selects the best-performing model for deployment.

Visualization&UserInterfaceLayer

- Presents forecasting results using dashboards, graphs, and interactive charts.
- Allows users to compare actual versuspredictedcrudeoilpricesinrealtime.
- Providesinsightsintomodelperformance, trends, volatility patterns, and error behavior.
- Actsasthefront-endinterfacefordecision makers, analysts, and researchers.

End-to-EndWorkflowSummary

- DataCollection→Preprocessing→Modeling →Training&Validation→Visualization
- Ensuresacomplete,modular,andscalable pipeline for crude oil price forecasting using Generative AI and deep learning

IV.ModelConfigurations

Baseline LSTM Model

AnLSTMnetworkisimplementedusing TensorFlow/Keras:

```
Model=Sequential()
model.add(LSTM(50,return_sequences=True, input_shape=(60, 1)))
model.add(LSTM(50)) model.add(Dense(1)) model.compile(optimizer='adam', loss='mean_squared_error')
```

- Inputshape**:**(time_steps,1)wheretime_steps =60.
- Hiddenunits:2stackedLSTMlayerswith50 units each.
- Output:Single neuron(Dense(1)) predicting the next-day price.
- Lossfunction:MeanSquaredError(MSE).
- Optimizer:Adam.

Transformer-BasedModel :

ATransformer-basedforecastingmodelisconfigured to capture long-range temporal dependencies that are difficult for standard LSTMs**:**

- Encoder–decoder or encoder-only stack with multi-head self-attention layers.
- Positional encodings added to represent time ordering.
- Feed-forwardlayersanddropoutusedfor regularization.
- Training objective: MSE on normalized prices,withAdamoptimizerandsimilarbatch size/horizon settings as the LSTM model

TimeGANforSyntheticDataGeneration

- Components:Embeddingnetwork,generator, discriminator, and supervised component to preserve temporal dynamics.

Training data: Preprocessed and normalized crude oil time series.

- Output: Synthetic sequences with similar temporalstructureandstatisticalcharacteristics as the real data.

Twoexperimentalsettingsareconsidered:

1. Withoutaugmentation–modelstrainedonlyon historical data.
2. With augmentation – models trained on a combination of historical and TimeGAN- generated sequences to assess robustness and performance gains.

Training Procedure

1. Initializationofmodelarchitecture(LSTM, Transformer, or TimeGAN).
2. Compilationusingasuitableloss(MSE)and optimizer (Adam).
3. Mini-batch training over multiple epochs (e.g., 10–50) with shuffled training sequences.
4. Regularization techniques such as dropout and early stopping to prevent overfitting.
5. Checkpointingofthebest-performingmodel weights based on validation loss.

EvaluationMetrics

To compare the forecasting performance of different models, the following metrics are computed on the test set:

- MeanAbsoluteError(MAE)
- RootMeanSquaredError(RMSE)
- MeanAbsolutePercentageError (MAPE)
- CoefficientofDetermination(R^2)

V.Hardware and Software Environment

ExperimentsareconductedinaPython environmentusingthefollowingtoolsand configurations:

- Programminglanguage:Python3.8+
- Corelibraries**:**
  - ➢ TensorFlow2.x/Keras(LSTM, Transformer, TimeGAN)
  - ➢ PyTorch(alternativeimplementationfor generative modeling)
  - ➢ Scikit-learn(preprocessing, metrics)
  - ➢ NumPy &Pandas(datahandlingand numerical computation)
  - ➢ Matplotlib&Seaborn(visualization**)**
- Development platforms: Jupyter Notebook / Google Colab and Anaconda-managed environments; Git/GitHub for version control.
- Operating systems: Windows 10/11 or Linux (Ubuntu recommended for deployment).

Hardware:

- ➢ Minimum: Inteli3CPU, 8 GB RAM, 256 GB storage.
- ➢ Recommended: Intel i5/i7 or Ryzen 5/7,16GBRAM,512GBSSD,and aCUDA-enabledNVIDIAGPU for accelerated training.

VI.Figures

Figure2:CrudeOil DataOverview

The figure presents key insights from the crude oil dataset. The price trend shows noticeable fluctuations over time, indicating market volatility. The histogram illustrates that most prices are concentrated within a mid-range, while the volatility plot highlights sudden spikes in market movement. The correlation heatmap shows strong relationships among the variables, supporting their importance for predictive modeling.

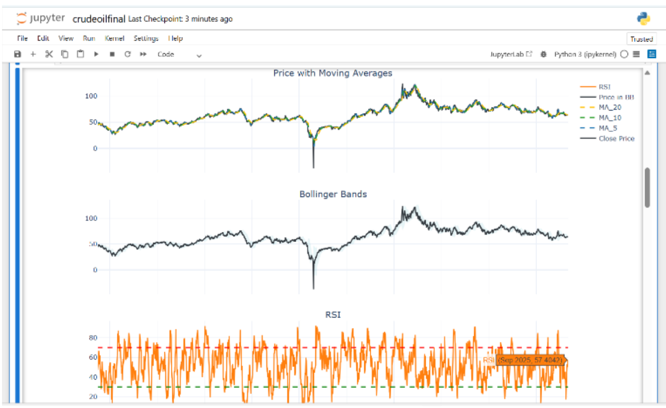

Figure3:TechnicalIndicatorAnalysis

The figure illustrates important technical indicators applied to crude oil prices. The moving averages (MA10, MA20, MA50) help identify overall market trends by smoothing price fluctuations. The Bollinger Bands show changes in market volatility, while the RSI plot highlights potential overbought and oversold conditions. Together, these indicators provide useful insights into trend, momentum, and volatility patterns for forecasting analysis.

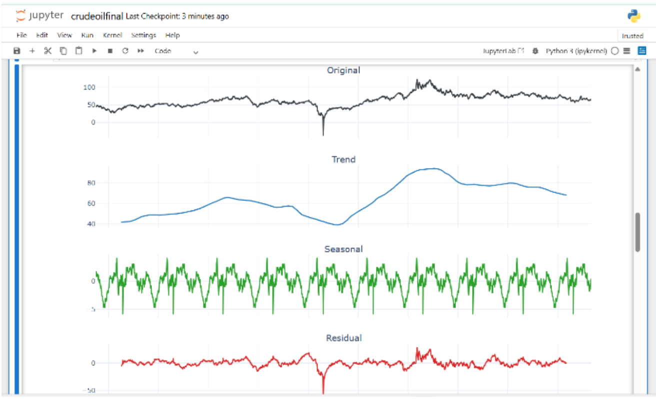

Figure4:TimeSeriesDecomposition

The figure presents the decomposition of crude oil prices into trend, seasonal, and residual components. The original series shows overall price fluctuations over time, while the trend component highlights the long-term market direction. The seasonal component captures repeating cyclical patterns, and the residual component represents irregular variations and unexpected market shocks. This decomposition helps in understanding the underlying structure of the data and improves forecasting accuracy by separating meaningful patterns from noise.

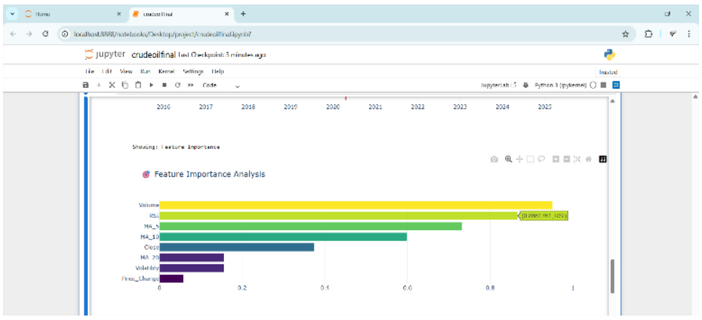

Figure5:FeatureImportanceAnalysis

The figure shows the importance of different features used for crude oil price prediction. Trading volume appears as the most influential feature, indicating its strong impact on price movements. Moving averages (MA_10, MA_20, and MA_50) also contribute significantly by capturing market trends, while indicators such as volatility and RSI provide additional insights into market momentum and price behavior.

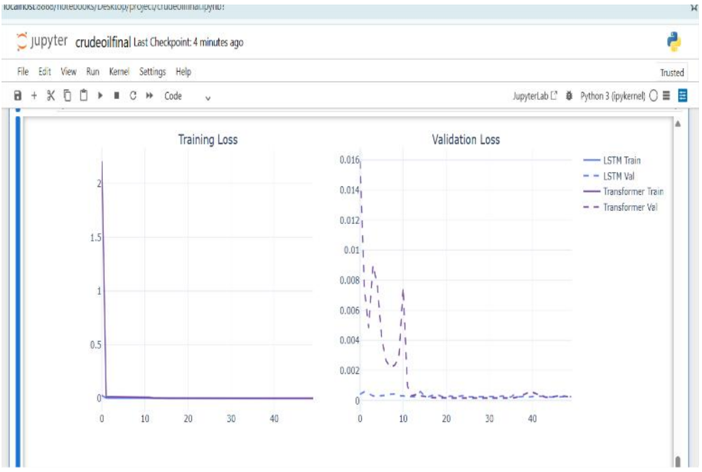

Figure6:ModelTrainingProgress

The figure compares the training and validation loss of the LSTM and Transformer models over multiple epochs. Both models show a rapid decrease in loss during early training, indicating effective learning. The Transformer model achieves smoother convergence and lower validation loss, suggesting better generalization and stability. In comparison, the LSTM model shows slightly higher fluctuations, reflecting greater sensitivity to market volatility. Overall, the results indicate that the Transformer model performs more effectively for crude oil price forecasting.

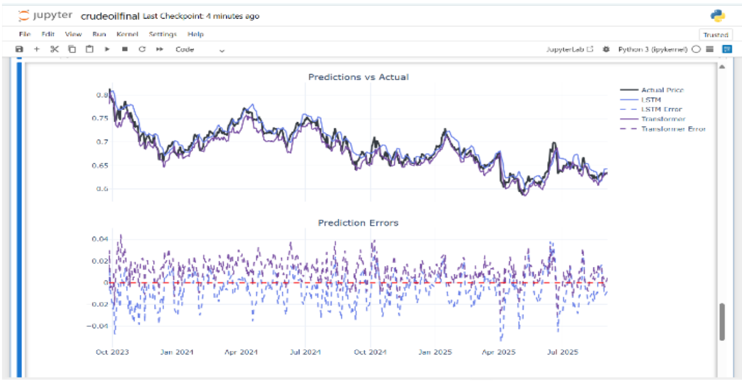

Figure7:PredictionAnalysis

The figure compares the actual crude oil prices with predictions from the LSTM and Transformer models. Both models follow the overall market trend, but the Transformer shows closer alignment with the actual values, especially during fluctuating periods. The prediction error plot further indicates that the Transformer produces smaller and more stable errors compared to the LSTM. These results demonstrate the Transformer model's higher accuracy and reliability in crude oil price forecasting.

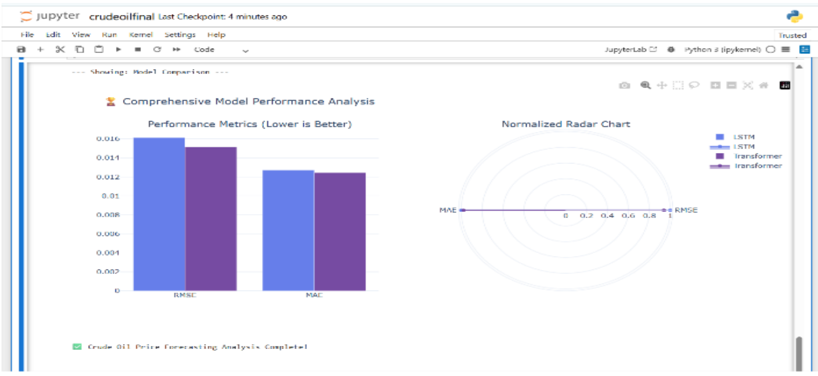

Figure7:ModelComparison

The figure compares the performance of the LSTM and Transformer models using MAE and RMSE metrics. The bar chart shows that the Transformer achieves lower error values, indicating better prediction accuracy. The radar chart also highlights the Transformer's more stable and consistent performance compared to the LSTM. Overall, the results demonstrate that the Transformer model provides more reliable crude oil price forecasting.

VII.CONCLUSION&FUTURE SCOPE

The "Generative AI for Crude Oil Price Forecasting" system successfully integrates advanced deep learning models—LSTM, Transformer, and TimeGAN—to address the complexities of predicting crude oil prices, which are characterized by high volatility, nonlinear behavior, and sensitivity to global events. The project demonstrates that combining predictive and generative techniques significantly improves forecasting accuracy compared to standalone statistical or deep learning methods. The Transformer architecture proved particularlyeffectiveduetoitsself-attentionmechanism, which captures long-range dependencies better than traditional sequential models. TimeGAN further enhanced model robustness by generating realistic synthetic time-series data that reduced overfitting and enriched the training distribution. Rigorous testing at unit,integration,system,andvalidationlevelsconfirmed the stability and reliability of the entire workflow. Performance metrics such as RMSE, MAE, and MAPE consistentlyindicatedstrongpredictivecapability,while visual comparisons showed close alignment between actual and predicted price movements. Overall, the system meets its objectives and provides a scalable, accurate, and user-friendly forecasting framework suitable for analysts, investors, researchers, and policymakers.

Lookingahead,theforecastingframeworkcanbefurtherimprovedinseveralways.Integratingadditionalexternal factors—suchasmacroeconomicindicators,geopolitical events, OPEC policies, exchange rates, market demand, and sentiment data—would enable the model to better capture real-world drivers of crude oil price volatility. Futureworkmayalsoinvolvedevelopingmoreadvanced hybrid architectures that combine LSTM, Transformer, TimeGAN, and other cutting-edge models to enhance multi-horizon forecasting accuracy.Interactive visual dashboards using tools like Plotly, Dash, or Tableau can offerricherandmoreinterpretableinsights.Furthermore, incorporating Explainable AI (XAI) techniques would improve transparency by highlighting key features and modelbehaviorsbehind eachprediction.Thesystemcan alsobeadaptedtoforecastothercommoditieslikenatural gas, gold, or agricultural products, thereby widening its practicalapplicability.Finally,deployingtheframework, improving computational efficiency with GPU/TPU acceleration, and enabling real-time forecasting would make the system even more powerful and accessible for large- scale industrial use.

REFERENCES

[1] Vapnik, V., Statistical Learning Theory, Wiley, 1995.Available: https://scholar.google.com/scholar

[2] Breiman,L.,"Randomforests,"Machine Learning,vol.45,no.1,pp.5–32,2001.Available:https://scholar.google.com/scholar

[3] Hochreiter, S.,andSchmidhuber, J.,"Longshort-term memory," Neural Computation, vol.9,no.8, pp.1735–1780, 1997.

[4] Hu, Z., Li, Y., and Wang, S., "Crude oil price prediction using CEEMDAN and LSTM-based deeplearningmodels,"EnergyEconomics,vol. 95, 2021.

[5] Yoon, J., Jarrett, D., and van der Schaar, M., "Time- series generative adversarial networks," NeurIPS, 2019. Available: https://scholar.google.com/scholar

[6] Hamilton, J. D., "Causes and consequences of the oil shock of 2007–08," Brookings Papers on Economic Activity, 2009.

[7] He,X.,Chen,X.,andHu,J.,"TemporalFusion Transformersforinterpretablemulti-horizon timeseries forecasting," AppliedIntelligence, 2023.Available: https://scholar.google.com/scholar

[8] Qin,Y.,Song,D.,Zhang,H.,Cheng,W.,andChen, H., "A dual-stage attention-based recurrent neural network for time series prediction," IJCAI,2017.Available: https://scholar.google.com/scholar