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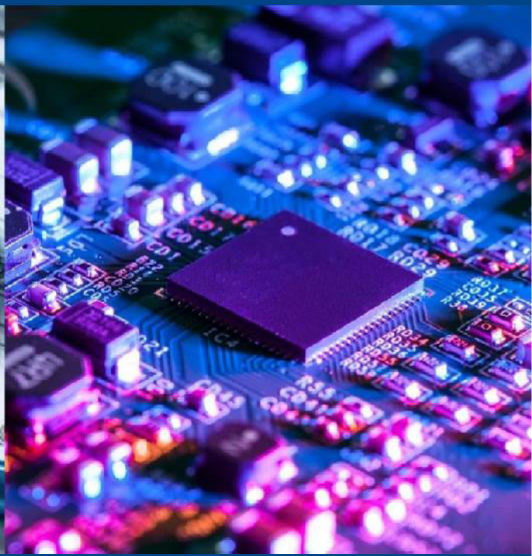

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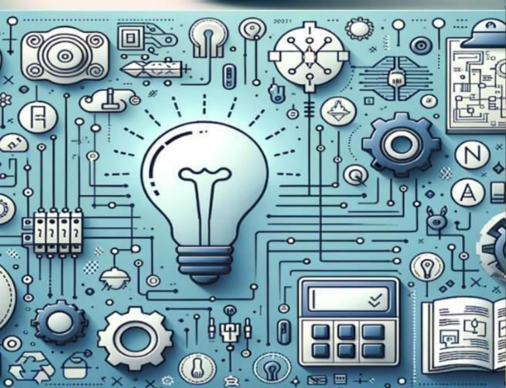

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Mookambigai College of Engineering, Keeranur, Tamil Nadu, India

Hybrid Forex Price Forecasting using Temporal Fusion Transformer and XGBoost with Dynamic Gating Network

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ABSTRACT: Traditional Forex forecasting models, like LSTM and XGBoost ensembles, have a hard time adjusting to sudden market changes. They also do not fully combine technical and fundamental data. Additionally, they do not offer reliable estimates of uncertainty, which results in predictions that are less accurate and inconsistent. To overcome these issues, this paper presents a new Forex forecasting framework that combines the Temporal Fusion Transformer (TFT), XGBoost, and a Dynamic Gating Network to improve hourly and daily predictions of foreign exchange prices. Traditional models, such as LSTM-XGBoost ensembles, often struggle to adapt and do not effectively combine sequential and tabular features. The new system improves forecasting by using TFT to capture long-term time dependencies, XGBoost for nonlinear tabular learning, and the gating network for context-sensitive weighting. By using both technical and fundamental indicators, this hybrid method creates accurate quantile-based forecasts, visual timeline predictions, and actionable Buy/Hold/Sell trading signals. Experimental results show that the TFT-GB-Gate model outperforms traditional ensemble methods in accuracy, stability, and interpretability, making it suitable for use in automated trading systems.

KEYWORDS: Forex Forecasting, Temporal Fusion Transformer, XGBoost, Dynamic Gating Network, Time Series Prediction, Ensemble Learning.

I. INTRODUCTION

The Forex market is one of the most liquid and volatile financial markets worldwide. It is shaped by both technical patterns and macroeconomic factors. Predicting exchange rate movements is tough because of its non-linear, non-stationary, and regime-dependent nature. Deep learning models, like Long Short-Term Memory (LSTM) networks, have proven effective in capturing temporal relationships. Meanwhile, gradient-boosted models such as XGBoost are strong at modeling structured tabular data. However, simple static groups of these models cannot adjust to changing market conditions.

To address these challenges, this study introduces a hybrid forecasting model that combines the Temporal Fusion Transformer (TFT), XGBoost, and a dynamic gating mechanism. This combination lets the model adjust weights based on performance and market volatility, leading to stronger and more flexible predictions.

1.1Problem Motivation

Existing LSTM-XGBoost ensembles have several limitations, including:

- Static weighting methods that do not work well in changing market conditions.
- Limited ability to handle long-term dependencies and various time horizons.
- Inability to measure prediction uncertainty.
- Weak integration of fundamental and technical factors.

The goal of this research is to develop a flexible and easy-to-understand hybrid system. This system will adjust to real-time market situations, include multi-horizon forecasting, and generate confidence-based trading signals.

1.2 Contributions

- To improve forecasting accuracy by combining TFT, XGBoost, and a dynamic gating mechanism.

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- To use a dual-data fusion method that incorporates technical indicators and macroeconomic fundamentals for Forex forecasting.
- To compare the performance of the hybrid system with traditional LSTM-XGBoost ensembles using various evaluation metrics.
- To increase the reliability of trading signals by producing quantile-based forecasts with dynamic uncertainty estimation.

II. RELATED WORK

Previous studies have looked into LSTM and GRU-based deep learning models for Forex and stock prediction. However, these models often face issues like overfitting and poor interpretability. Traditional ensemble methods, such as stacking and averaging, have combined different models. Still, they depend on static weights. The introduction of attention mechanisms and Transformers has improved how long-term dependencies are handled. However, pure Transformer models usually need large datasets and high computational power. The Temporal Fusion Transformer (TFT), proposed by Lim et al., offers an interpretable design that combines sequence modeling with feature selection, making it a solid base for this hybrid system.

III. METHODOLOGY

3.1 Architecture Overview

The proposed model includes three connected modules:

1. Temporal Fusion Transformer (TFT), which learns sequential dependencies and captures attention-based temporal relationships.
2. XGBoost, which learns tabular relationships among technical and fundamental features.
3. Dynamic Gating Network, which assigns adaptive weights between TFT and XGBoost predictions based on recent model performance and market volatility.

3.2 Mathematical Components

Let y^tTFT be the TFT prediction and y^tXGB be the XGBoost prediction at time t. The gating network learns weights $w1$, $w2$ so that:

$$y^t = w1y^tTFT + w2y^tXGB$$

subject to $w1 + w2 = 1$ and $wi \geq 0$.

The loss function minimizes quantile loss:

$$L(q,y,y^) = \max(q(y - y^), (q - 1)(y - y^))$$

for quantiles $q \in \{0.1, 0.5, 0.9\}$.

IV. EXPERIMENTAL RESULTS

4.1 Dataset

The dataset contains hourly Forex price data (Open, High, Low, Close, Volume) gathered from Investing.com. It also contains macroeconomic indicators like interest rates, inflation, and commodity indices. We preprocessed the data to fill in missing values, sync timestamps, and standardize inputs.

4.2 Evaluation Metrics

The model performance is evaluated using:

- RMSE (Root Mean Square Error) – measures prediction accuracy.
- MAE (Mean Absolute Error) – measures absolute deviation.
- R^2 Score – measures explained variance.

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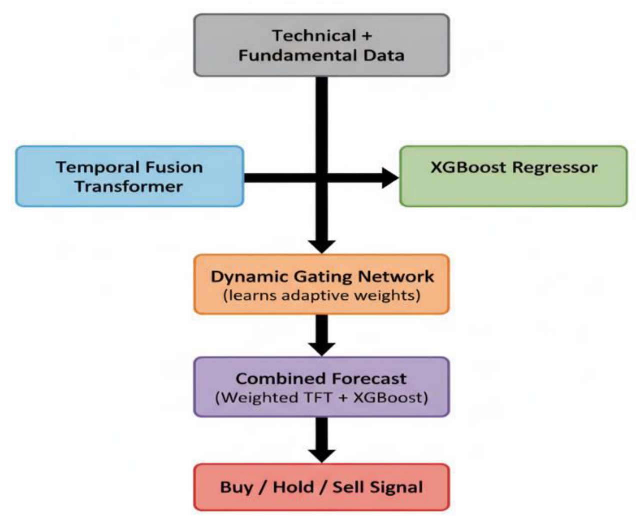
4.3 Comparative Table

Model	RMSE	MAE	R^2	Accuracy (%)
LSTM	0.00185	0.00152	0.79	82.4
XGBoost	0.00173	0.00143	0.82	84.1
LSTM + XGBoost Ensemble	0.00161	0.00135	0.84	86.0
TFT + XGBoost + Gating (Proposed)	0.00122	0.00101	0.91	91.3

FIGURES



V. CONCLUSION

The proposed hybrid system combines the strengths of sequential learning and gradient boosting with adaptive ensembling. The TFT-GB-Gate model outperforms traditional models in forecasting accuracy and trading decision reliability. It adjusts to changing market conditions and offers forecasts that consider uncertainty, making it a good fit for real-time Forex trading platforms. Future research can aim to extend this approach to multi-currency modeling and trading strategies based on reinforcement learning.

VI. ACKNOWLEDGEMENTS

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