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A Hybrid CNN-Bi-LSTM Based Model for Gold Price Forecasting Using Smart Money Concepts

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Abstract: ***Gold price forecasting is challenging because of frequent price changes and complex market patterns. Existing forecasting models mainly focus on historical price data and may not consider important market structure information. To address this limitation, this study presents a gold price forecasting system that combines CNN-Bi-LSTM with Smart Money Concepts (SMC). The proposed approach aims to improve prediction by learning price patterns and analysing market information, such as swing highs, swing lows, liquidity zones, Break of Structure (BOS), and Change of Character (CHoCH). The system compares different forecasting models with traditional methods using mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE) and directional displays of market patterns, predicted prices and model performance. The main contribution of this study is the evaluation of whether SMC-based market information can improve gold price forecasting compared with models that rely only on historical prices. This approach can help assess the value of combining market structure analysis with deep learning for more accurate forecasting.***

Index Terms: Gold Forecasting, CNN, Bi-LSTM, Smart Money Concepts, Deep Learning and Time Series.

I. INTRODUCTION

Gold is one of the important precious metals in the global financial market. Its price changes frequently according to economic conditions, market demand, inflation, and investor behaviour so it makes the accurate forecasting challenging. Traditional forecasting methods mainly depend on historical price data, while deep learning techniques such as convolutional neural networks (CNN) and bidirectional long short-term memory (Bi-LSTM) can learn complex patterns and relationships in price movements. Depending only on historical prices may limit the ability of forecasting models to capture main market structure information. To address this limitation, this study proposes a gold price forecasting framework that integrates Smart Money Concepts (SMC) with CNN-Bi-LSTM. SMC identifies market structure information, including swing highs, swing lows, liquidity zones, Break of Structure (BOS), and Change of Character (CHoCH). By combining these features into the forecasting process, the proposed approach aims to improve prediction performance and the accuracy compared with models that use historical prices alone. The dashboard displays historical prices, market structure patterns, predicted prices, and model evaluation results. Performance is assessed using mean absolute error (MAE), root mean squared error (EMSE), mean absolute percentage error (MAPE), and directional accuracy to evaluate the contribution of SMC to gold price forecasting.

The key contributions of this study are:

1) Hybrid CNN-Bi-LSTM architecture for metals price forecasting
2) Integration of Smart Money Concepts (SMC) into deep learning-based feature engineering.
3) Improved forecasting performance compared to traditional and hybrid models.
4) Enhanced interpretability through incorporation of market structure insights.

II. MOTIVATION AND OBJECTIVES

A. Motivation

Gold price forecasting is challenging because market prices change frequently owing to economic conditions and market behaviour. Existing forecasting models mainly rely on historical price data, which may not forecast models mainly rely on historical price data, which may not fully capture important market structure patterns. Deep learning models, such as CNN-Bi-LSTM can learn complex price movements, but their performance can be improved by incorporating additional market information. Smart Money Concepts (SMC) identifies market patterns through swing highs, swing lows, liquidity zones, Break of Structure (BOS), and Change of Character (CHoCH). Integrating these features with CNN-Bi-LSTM provides an opportunity to capture more information about market movements and improve forecasting performance. Hence this study investigates the impact of SMC features on gold price prediction and presents the results through an interactive dashboard

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B. *Objectives*

1) To design and implement a gold price forecasting system using CNN-Bi-LSTM and historical gold price data.
2) To design and implement a gold price forecasting system using CNN-Bi-LSTM and historical gold price data.
3) To identity market structure patterns using SMC indicators which includes swing highs, swing lows, liquidity zones, BOS and CHoCH.
4) To integrate SMC-derived features into the forecasting model to improve prediction performance.
5) To compare the proposed approach with existing forecasting methods, including persistence and moving average models.
6) To evaluate the forecasting performance using MAE, RMSE, MAPE and directional accuracy across multiple prediction horizons.
7) An interactive dashboard was developed to display historical prices, market structure patterns, predicted price and model performance.

III. LITERATURE REVIEW

Amini and Kalantari [1] introduced a convolutional neural network – bidirectional long short-term memory (CNN-Bi-LSTM) model that automatically tunes its parameters for gold price forecasting. The study used only past gold prices as input so it is still unclear how other market structure features could help.

Foroutan and Lahmiri [2] examined deep learning models for predicting crude oil, gold, and silver prices. Their work showed that comparing architectures and the order of input data is essential for judging forecasting performance.

Another study [3] paired CNN-LSTM with the Gramian Angular Field (GAF), a technique that turns time-series data into pictures to spot patterns in gold prices. These investigations reveal that deep learning can be powerful.

Building on these findings this project examines the combination smart money concepts (SMC) with a CNN-Bi-LSTM model for gold price forecasting. This approach studies market structure signals such as swing highs, swing lows, liquidity zones, break of structure (BOS) and change of character (CHoCH). The results are compared with forecasting methods using measures such as MAE, RMSE, MAPE and directional accuracy for several forecast periods. The goal is to determine SMC derived features improve gold price forecasting.

Table 1: Comparison of Existing Methods in Financial forecasting

Method	Key Features	Strengths	Limitations	Typical Performance Insight
ARIMA	Statistical model using past values and errors	Simple, interpretable, good for linear trends	Cannot capture non-linear patterns, poor with volatility	Performs reasonably on stable data but struggles with complex dynamics (arXiv)
Machine Learning	Uses engineered features and non-linear mappings	Captures non-linear relationships	Requires heavy feature engineering, weak temporal modelling	Better than statistical models but limited for sequential data
LSTM	Recurrent neural network with memory cells	Captures long-term dependencies	Unidirectional learning, limited context	Outperforms ARIMA significantly in financial prediction (ResearchGate)
Bi-LSTM	Processes sequence forward and backward	Better context understanding	Higher complexity, slower training	Provides improved accuracy over LSTM (arXiv)
CNN	Extracts local spatial patterns	Good for short-term trend detection	Cannot model long-term dependencies alone	Effective for feature extraction but incomplete alone (ResearchGate)
CNN–LSTM	Combines spatial + temporal learning	Strong performance in time series forecasting	Still lacks domain knowledge (market structure)	Reduces prediction error vs standalone models (MDPI)
Hybrid ARIMA–CNN–LSTM	Combines linear + non-linear modelling	High accuracy, captures full dynamics	Complex, still data-driven only	Significant RMSE reduction compared to individual models (Springer)
Existing Deep Learning Models	Use technical indicators +price data	High predictive power	Black-box nature, low interpretability	Good accuracy but lacks explainability

IV. METHODOLOGY

The workflow used in the proposed gold-price forecasting system are as following steps:

1) Data Collection: Historical gold futures data were gathered for the chosen study period. The data were recorded in four-hour candlestick intervals. The data include open, high, low and close prices.
2) Data preprocessing: The collected data were examined for missing values, duplicate entries, and inconsistencies. The data were then organized for forecasting. It was split chronologically into training and testing sets.
3) SMC Feature Extraction: Smart money concepts are applied to identify market structure patterns. These patterns include swing highs, swing lows, liquidity zones, break of structure (BOS), and change of character (ChoCH).
4) Feature Preparation: Historical price data and SMC-derived features are prepared as inputs for the model. The features are matched to their corresponding timestamps to ensure that no future information is used during forecasting.
5) CNN-Bi-LSTM Model Development: A CNN component was used to detect patterns within the input sequences. A Bi-LSTM component captures the dependencies in price movements to predict gold prices.
6) Baseline Model Comparison: The proposed model is compared to persistence and moving- average forecasting methods. CNN-Bi-LSTM models, without SMC features are evaluated for performance.
7) Multi-horizon forecasting: Predictions are generated for multiple time horizons, including h1, h3, and h6, to assess how well the model performs across forecasting intervals.
8) Performance Evaluation: Model performance was measured using the mean absolute error (MAE) and root mean squared error (RMSE). Directional accuracy. These metrics were used to compare the results of all models.
9) Visualization and Analysis: Actual and predicted gold prices are plotted on charts. This allows users to observe forecasting behaviour and compare model outputs visually.
10) Interactive Dashboard: The system offers a dashboard that displays historical gold prices, SMC market structure indicators, prediction results, and evaluation metrics. This enables convenient analysis.

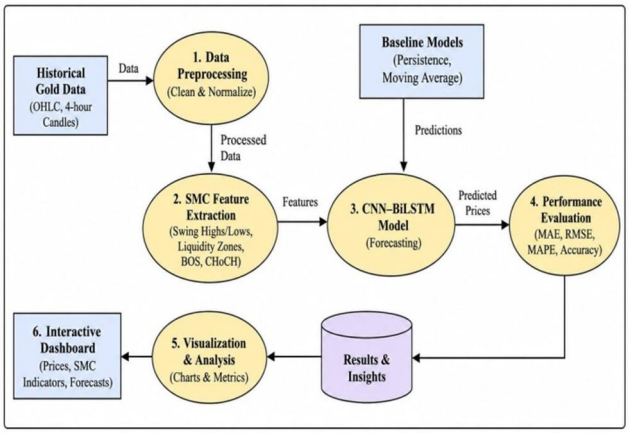

Fig 1. Workflow of the proposed Gold Price Forecasting System

V. SYSTEM ARCHITECTURE

The proposed system is designed to predict gold prices by analysing market data and market structure patterns. It has data collection, preprocessing, SMC analysis, price forecasting, performance evaluation, and visualization modules. These modules work together to study price changes, make predictions, and check how good the quality. The system starts by gathering gold futures data that includes open, high, low, and close (OHLC) values every four hours. The data are then prepared analysis. The SMC modules find swing highs, swing lows, liquidity zones, break of structure (BOS), and change of character (CHoCH) to show market structure details. The cleaned price data and SMC -based features are provided to the CNN-Bi-LSTM model if they are part of the model inputs. The CNN part finds patterns in the data, whereas the Bi-LSTM part understands how prices change over time to predict future gold prices. The predictions are compared with methods, such as persistence and moving-average models. The performance is checked using MAE, RMSE, MAPE, and directional accuracy for the chosen prediction times. Finally, a dashboard shows gold prices, SMC indicators, predicted prices, and evaluation numbers. This helps users understand how the model works and compare its performance does. The system was designed to determine whether adding SMC-based features helps more, than models that use past price data.

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VI. EXPERIMENTAL RESULTS

The proposed system was tested using real gold price data with a 4-hour timeframe. During testing the CNN-Bi-LSTM model was able to capture the overall movement of gold prices, and its predicted values followed a pattern similar to the actual market prices. Based on the reported MPE values, the forecasting results correspond to 99.59% for one candle, 99.26% for three candles, and 98.90% for six candles, giving an average MAPE-derived forecasting score of 99.25%. The system also used smart money concepts (SMC) to identify market structures (BOS), change of character (CHoCH), and liquidity zones. The prediction graphs showed similar price movement patterns in the models developed with and without SMC. For directional prediction the CNN-Bi-LSTM model with SMC recorded 53.2% accuracy at the six-candle horizon, while the model without SMC recorded 51.2% at the one-candle horizon. The historical evaluation also showed 97.59% accuracy for SMC zone target classification and 63.51% for reaching the nearest market price level. These results relate to different prediction tasks and are therefore evaluated separately. The dashboard presents the predicted price movements and nearby market levels through graphs and probability estimates, helping users understand to the possible behaviour of the gold market.

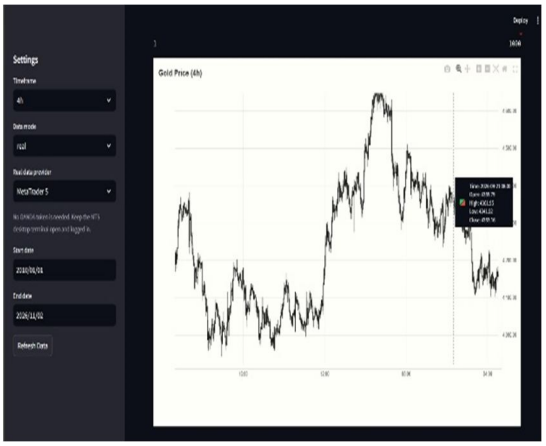

Fig 2. Historical gold price movement visualization.



Fig 3. SMC analysis of gold price movements using daily (1D) timeframe.

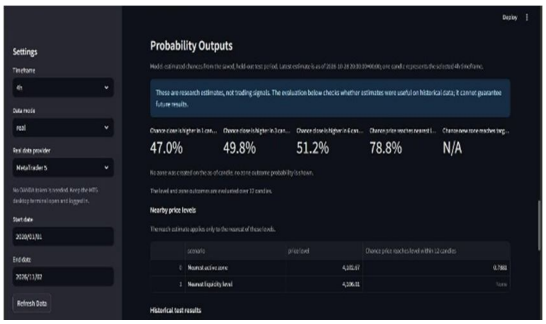

Fig 4. Probability-based gold price prediction results.

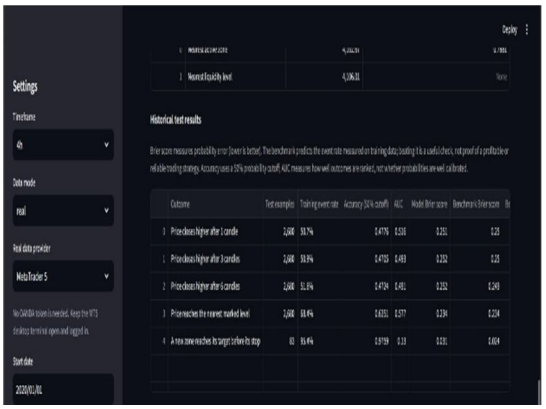

Fig 5. Historical model performance evaluation results.

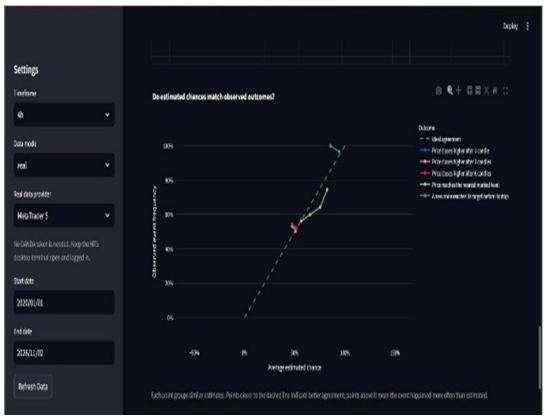

Fig 6.Probability calibration curve for model predictions

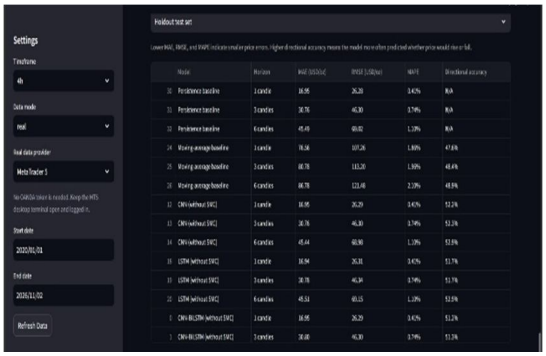

Fig 7. Comparative performance evaluation of prediction models.

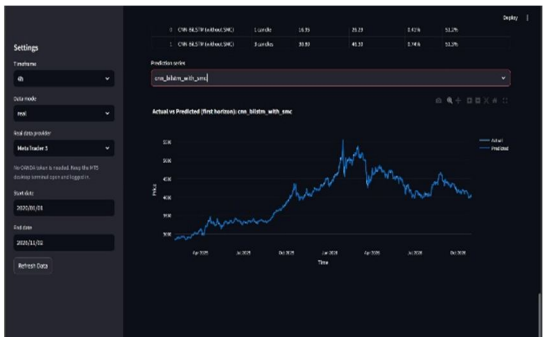

Fig 8. Actual vs. Predicted gold price comparison.

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VII. CONCLUSION

This study presents a gold price forecasting system that uses CNN-Bi-LSTM and smart money concepts (SMC). The proposed approach mixes gold price data with market structure information. This market structure information includes swing highs, swing lows, liquidity zones, break of structure (BOS), and change of character (ChoCH). We used these to determine how they help predict gold prices. The system also checks forecasting models by looking at MAE, RMSE, MAPE, and directional accuracy. It does this for different prediction horizons. An interactive dashboard shows a view of historical prices, market structure patterns predicted prices and how well the models perform. We will decide how useful it is to add SMC features by doing experiments. In this study we will try to improve the forecasting model, test it on more datasets and look at using more market indicators.

VIII. ACKNOWLEDGMENT

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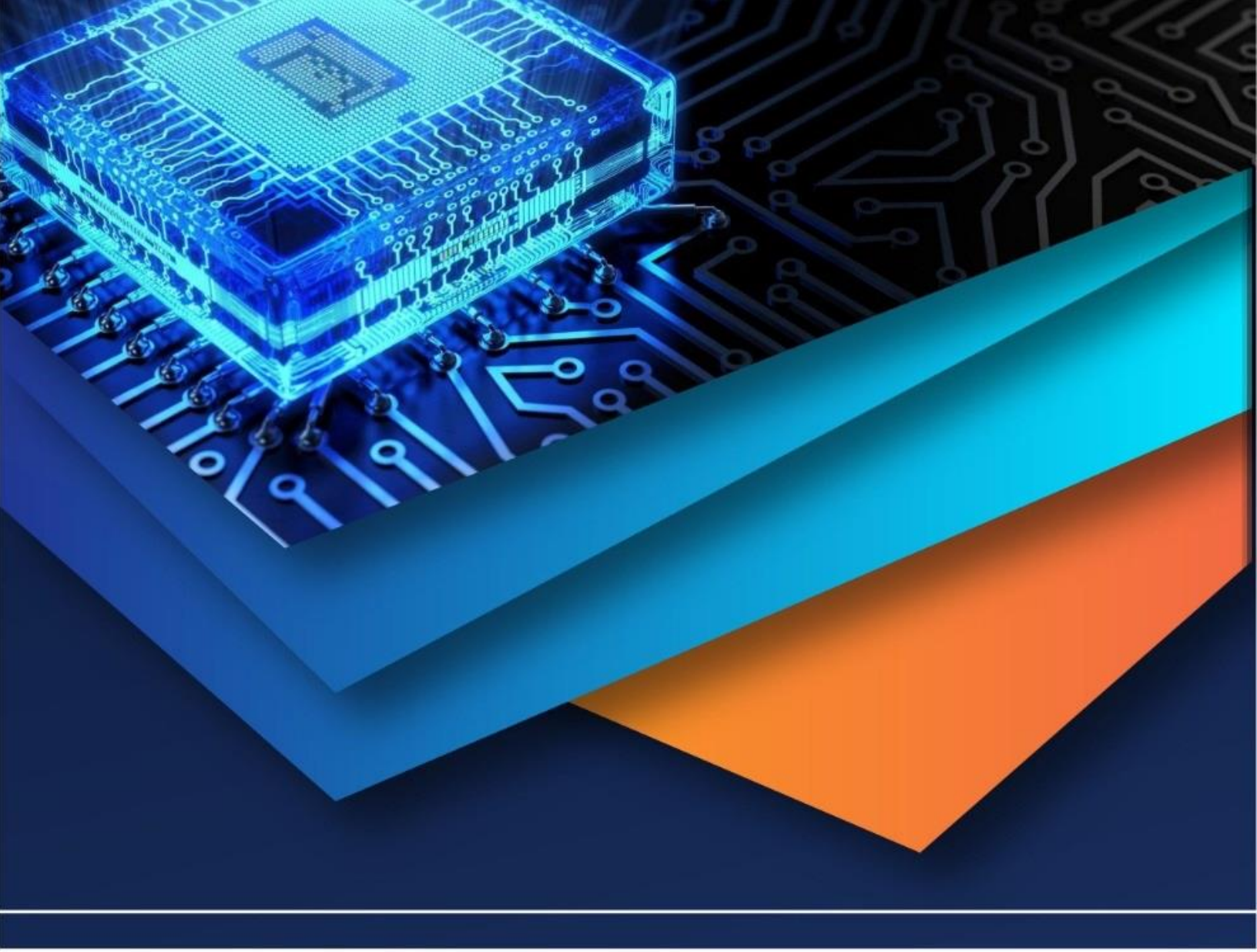

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