Advanced Time Series Modeling for High-Risk Financial Instruments Using VRA-Enhanced Machine Learning

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ABSTRACT

Financial markets face frequent volatility and rapid regime shifts, which lead to uncertainty and risk for investors and financial institutions. This can be addressed by building a model that remains reliable under changing conditions and detects rare but impactful high-risk events. However, building such a model constitutes a great challenge. Individual Machine Learning (ML) models can capture complex nonlinear patterns. However, they often face a trade-off between recall and precision as models optimized for recall tend to produce many false alarms, whereas models with higher accuracy may miss significant risk episodes. The current study addresses this issue by proposing the Volatility Risk Analyzer (VRA), a hybrid prediction framework combining both supervised and unsupervised learning techniques. Unsupervised regime detection is performed using K-means clustering, and Long Short-Term Memory (LSTM) networks are utilized to model temporal dynamics in financial time-series data. The clustering outputs are integrated employing a hybrid training technique to exploit their complementary strengths. The proposed framework is evaluated using an external dataset of five years of ICICI Bank OHLCV stock data, supplemented with widely deployed technical indicators such as Moving Averages, Moving Average Convergence Divergence (MACD), Rate of Change (ROC), and Williams %R. The results indicate that combining supervised and unsupervised learning enhances volatility risk prediction, offering a novel contribution for both academic research and real-world risk management applications.

Keywords-volatility risk prediction; LSTM, K-means; financial time series; volatility risk

I. INTRODUCTION

Unexpected shifts in financial markets often lead to significant capital losses due to sudden increases in volatility. As a result, investors and financial institutions devote considerable effort to accurately forecasting volatility for effective risk management. However, volatility prediction remains a challenging task because of market uncertainty and the nonlinear nature of financial time-series data. Moreover, traditional econometric models, such as the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model [1], can capture time-varying volatility, but they rely on assumptions of linearity and stationarity, which limit their ability to model complex dependencies and rapid market dynamics in real-world financial systems.

To address the limitations, approaches such as Machine Learning (ML) and quantitative hybrid approaches have gained attention in financial research, including models like Long Short-Term Memory (LSTM) networks, which are well-suited for nonlinear temporal patterns. Moreover, previous studies have demonstrated that LSTM–GARCH hybrid models often outperform standalone econometric methods. For example, authors in [2] reported significant improvements in prediction error using a GARCH–LSTM framework. Authors in [3] achieved over 92% accuracy when applying an LSTM–

GARCH model to the S&P 500 index, while authors in [4] reported robust performance during periods of economic instability. These findings highlight the growing potential of deep learning-based volatility modeling. Additionally, the proposed approach focuses on the design and development of a novel hybrid framework for identifying high- and medium-risk conditions in financial markets. The introduced Volatility Risk Analyzer (VRA) model integrates both supervised and unsupervised learning to identify both temporal dynamics and regime changes in market behavior. The framework combines LSTM-based volatility prediction and K-means for regime detection. This integrated approach enables VRA to improve predictive accuracy while maintaining high recall, which is more balanced and reliable for practical financial risk forecasting.

ARCH and GARCH econometric models dominate financial market volatility prediction. These conditional variation models are employed for market returns. However, linearity and stationarity assumptions limit their applicability to structural discontinuities and abrupt regime shifts. Empirically, GARCH-class models perform well in relatively stable regimes but degrade around abrupt volatility spikes and structural breaks [5]. Mixture and hybrid variants address some of these gaps by combining GARCH with deep learning [6]. Modern ML models can capture long-term, nonlinear dependencies. Sequential learning makes LSTM and GRU architectures popular [7]. In volatile markets, LSTM outperforms standard econometric models in volatility forecasting. However, solo ML models have limitations. Authors in [8] found that tree-based algorithms such as XGBoost had superior short-term accuracy on S&P 500 data, whereas LSTM and GRU better represented temporal connections. Long-range correlations are better captured by attention-based LSTM variations than simpler recurrent models. In financial forecasting, tree-based ensemble models such as Random Forest (RF) and XGBoost are popular for their durability and nonlinear interaction handling. Because sequence information is ignored, temporal tasks are performed poorly relative to recurrent neural networks. XGBoost has been paired with LSTM or CNN-LSTM to address this issue [9, 10]. While ensemble techniques have been applied to exchange rate prediction [11], their performance may degrade when applied to rapidly changing volatility regimes without temporal modeling.Unsupervised clustering algorithms have been used to predict financial volatility alongside supervised models. The ability to detect abnormalities and organize data in noisy, high-dimensional situations makes DBSCAN popular. DBSCAN is effective for volatility clusters since it detects regime transitions. Nevertheless, it rarely appears in financial forecasting supervised prediction models. Clustering is typically used in research for anomaly detection or preprocessing without prediction frameworks [12].

Econometric, ML, and deep learning hybrid models are an emerging research topic that uses complementary strengths. While the hybrid LSTM-XGBoost and LSTM-SVM models outperform standalone models in financial forecasting, the CNN-LSTM with attention mechanism and XGBoost predicted more accurately highly volatile markets. Authors in [13] developed a hybrid architecture using VMD, LSTM, GRU, and ANN to improve stock index accuracy and risk management. However, most hybrid models are supervised. Their accuracy measurements never address recall, indicating rare but high-impact volatility episodes. The present study adds VRA to hybrid modeling. Contrary to prior research, VRA favors supervised LSTM predictions over unsupervised K-means clustering. To address a research need, this unique combination increases the performance of pattern recognition algorithms.

II. METHODOLOGY

A hybrid volatility-risk pipeline employing financial time-series preprocessing, supervised ML, and unsupervised clustering is presented in this study. The database contains five-year ICICI Bank OHLCV stock data, yielding approximately 110,000 observations [14]. Preprocessing included normalization using MinMaxScaler and forward fill imputation for missing values. Since OHLCV data cannot capture nonlinear dynamics, technical indicators were created to expand feature space using Moving Average Convergence Divergence (MACD), MA16, Rate of Change (ROC), Williams %R, VWMA, and LRMA. The labeling strategy is generally used in financial strategies, such as Low risk = Vol < 33rd percentile, medium risk = 33rd - 66th percentile, and high risk = > 66th percentile. Indicator-driven forecasting has been validated in commodity markets [15], enhanced with external signals such as Google Trends [16], and extended to multi-input LSTM architectures for stock prediction [17]. After indicators and hyperparameters are prepared, the workflow is separated into two coordinated pipelines. On the supervised branch, an ML trainer fits four algorithms—LSTM, Linear Regression (OLS), RF, and XGBoost—on chronologically ordered training data and tests on a walk-forward validation to preserve temporal causality. The unsupervised branch learns density structure and regime groupings in the same indicator space using K-means clustering, finding clusters using the elbow method (optimized way) or a user input. In this study, a target number of clusters of 20 was chosen, taking one quarter as a trading session (4 sessions per trading day) as historical data were available for 5 years. Repeatability and live scoring are possible with trained parameters and scalers. This recurrent structure preserves long-range context and overcomes vanishing gradients. To avoid missing risk events, LSTM outperforms static learners in volatility prediction [18]. OLS is an interpretable linear baseline with lower-bound performance and indicator space linear separability requirements. Multiple decorrelated decision trees are trained on bootstrap samples with feature subset selection, and majority vote estimates class probability, creating nonlinearity and variance reduction in RF. Gradient boosting is used with second-order loss approximation, L1/L2 regularization, and shrinkage fits consecutive trees' residuals to enhance discrimination and calibrate probability. On structured, modest-dimension datasets, RF and XGBoost outperform OLS in financial prediction and related tabular domains. Since learners use complementary technical features and macro signals, commodity forecasting and hybrid-volatility studies support a broad model set. The clusters identified are subsequently transformed into one-hot encoding to form a dataset from these pre-trained clusters, which is then used to train the models, giving a clear indication of regimes for ML.

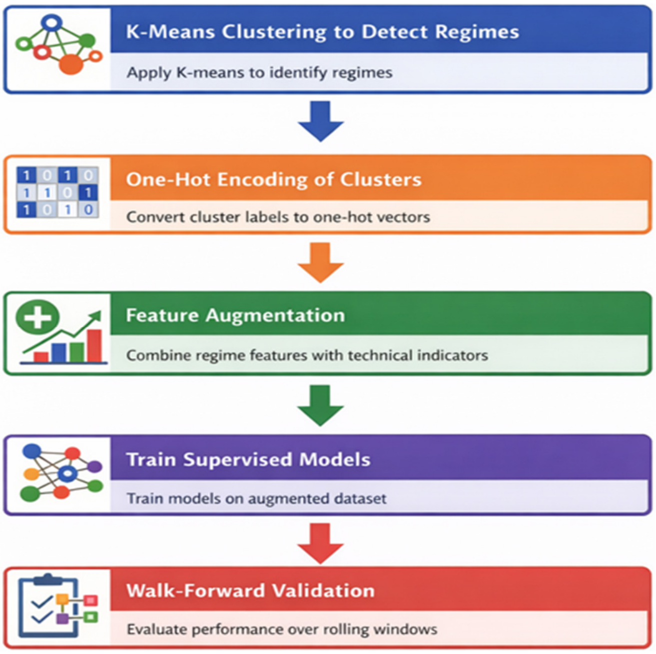

Fig. 1. VRA pipeline for risk analysis.

Figure 1 illustrates the VRA pipeline for volatility risk analysis. It begins with regime detection via K-means clustering, followed by one-hot encoding and feature augmentation. Supervised models are then trained on the enriched dataset and evaluated using walk-forward validation for robustness. This integration ensures that regime awareness is embedded in the prediction process. Table I summarizes the models used in this research. While LSTM provides temporal sensitivity and sequence memory, OLS gives transparency and a linear benchmark, and RF lowers variance and robustness to nonlinear interactions. XGBoost provides highly structured feature accuracy and error-correction. Tree ensembles and gradient boosting dominate static accuracy metrics on tabular data in volatility and return prediction studies, while recurrent models capture temporal impacts and tail behavior that static learners miss. The adaptable, interpretable, and scalable VRA predicts financial risk using sequential modeling, linear and nonlinear supervised learners, and clustering-based regime detection. The architecture provides operational choices along the recall–accuracy spectrum and supports generalization across assets and market conditions using complementary inductive biases—LSTM temporal memory, tree ensemble partitioning and boosting, OLS linear interpretability, and K-means unsupervised structure.

TABLE I. SUMMARY OF MODELS USED IN VRA

Model / algorithm	Purpose in VRA	Advantages
LSTM	Models time-series volatility trends	Captures sequences and nonlinear patterns
OLS	Provides a simple baseline	Easy to interpret and compare
RF	Handles nonlinear classification	Reduces overfitting and increases stability
XGBoost	Boosts the model for strong prediction	High accuracy and efficient learning
SVM	Classifies regimes and risk states using margin-based separation	Robust to overfitting
K-means	Detects hidden regimes in financial data without labels.	Simple, efficient, and useful for unsupervised clustering

III. RESULT AND DISCUSSION

The results are provided in four stages, namely baseline LSTM model evaluation, unsupervised K-means clustering assessment, one-hot encoding of clusters, and model retraining. By appending one-hot encoded regime features to the technical indicators, the supervised learners gained regime awareness.

TABLE II. TECHNICAL INDICATORS AND PARAMETERS

Indicator	Category	Parameters	Output	Formula / method
Relative Strength Index (RSI)	Momentum	period = 14	RSI	$RSI = 100 - (100 / (1 + RS)), RS = SMA\,(Gain, 14) / SMA\,(Loss, 14)$ Range: 0–100
Stochastic RSI	Momentum	rsi_period = 14 stoch_period = 14	StochRSI	$StochRSI = ((RSI - RSI\_min) / (RSI\_max - RSI\_min)) \times 100$, Min/Max computed over stoch_period rolling window, Range: 0–100
MACD	Trend	fast_period = 12 slow_period = 26 signal_period = 9	MACD MACD_signal MACD_histogram	$MACD = EMA\,(Close, 12) - EMA\,(Close, 26), Signal = EMA\,(MACD, 9), Histogram = MACD - Signal$
Simple Moving Average (SMA)	Trend	period = 16	MA_16	$MA = Mean\,(Close, 16)$, Rolling window arithmetic mean of last 16 close prices
ROC	Momentum	period = 10	ROC	$ROC = ((Close - Close[t-10]) / Close[t-10]) \times 100$, Percentage change over 10 periods
Williams %R	Momentum	period = 14	Williams_R	$\%R = ((HH - Close) / (HH - LL)) \times (-100)$, HH = Highest High over 14 periods, LL = Lowest Low over 14 periods, Range: −100 to 0
Volume Weighted Moving Average (VWMA)	Volume	period = 14	VWMA	$VWMA = \Sigma(Close \times Volume, 14) / \Sigma\,(Volume, 14)$, Volume-weighted rolling sum over 14 periods
Linear Regression Moving Average (LRMA)	Trend	period = 14	LRMA	Fits a least-squares linear regression line to the last 14 close prices. Returns predicted value at the last point: $y = slope \times (n-1) + intercept$
Historical volatility	Volatility	period = 21	Volatility	$Vol = StdDev(ln(Close[t] / Close[t-1]), 21)$, Standard deviation of log returns, over a rolling 21-period window

TABLE III. CONFUSION MATRIX (LSTM WALK-FORWARD MONTHLY WINDOW -13)

Standard LSTM				**Hybrid LSTM (K-Means 20)**			
Actual \ predicted	Low risk	Medium risk	High risk	Actual \ predicted	Low risk	Medium risk	High risk
Low risk	9,442	25,659	2,037	Low risk	16,611	18,508	2,019
Medium risk	6,231	19,526	8,987	Medium risk	6,412	18,182	10,150
High risk	3,276	8,219	10,522	High risk	2,782	7,300	11,935

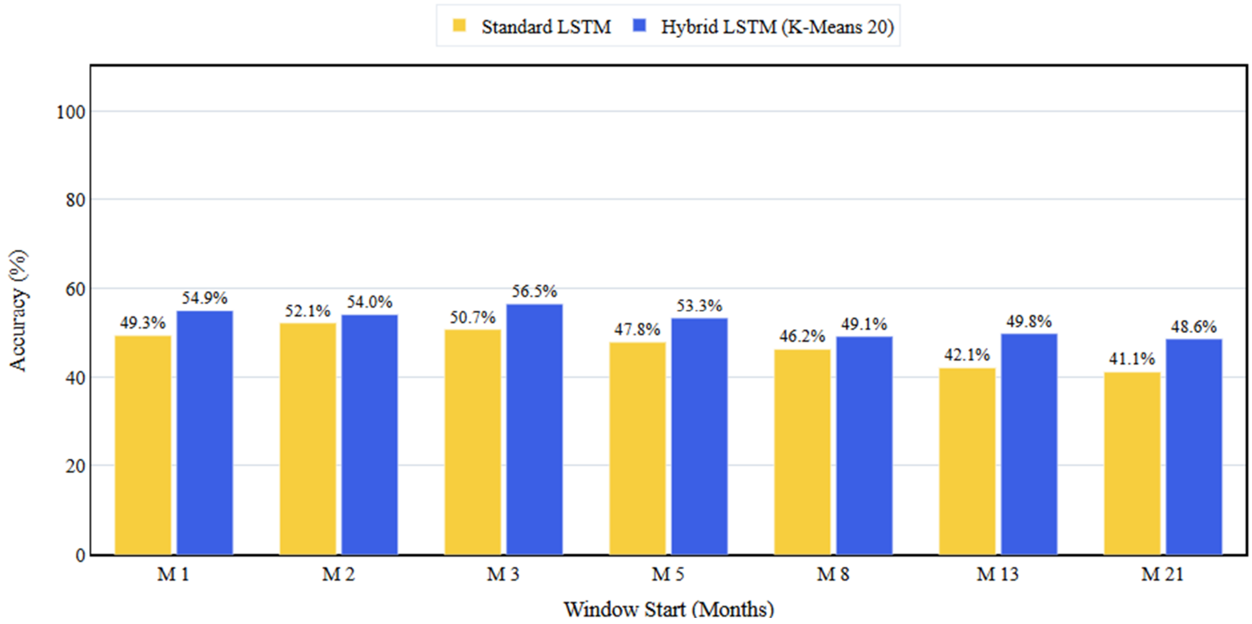

Fig. 2. Accuracy for standard vs hybrid LSTM modeling.

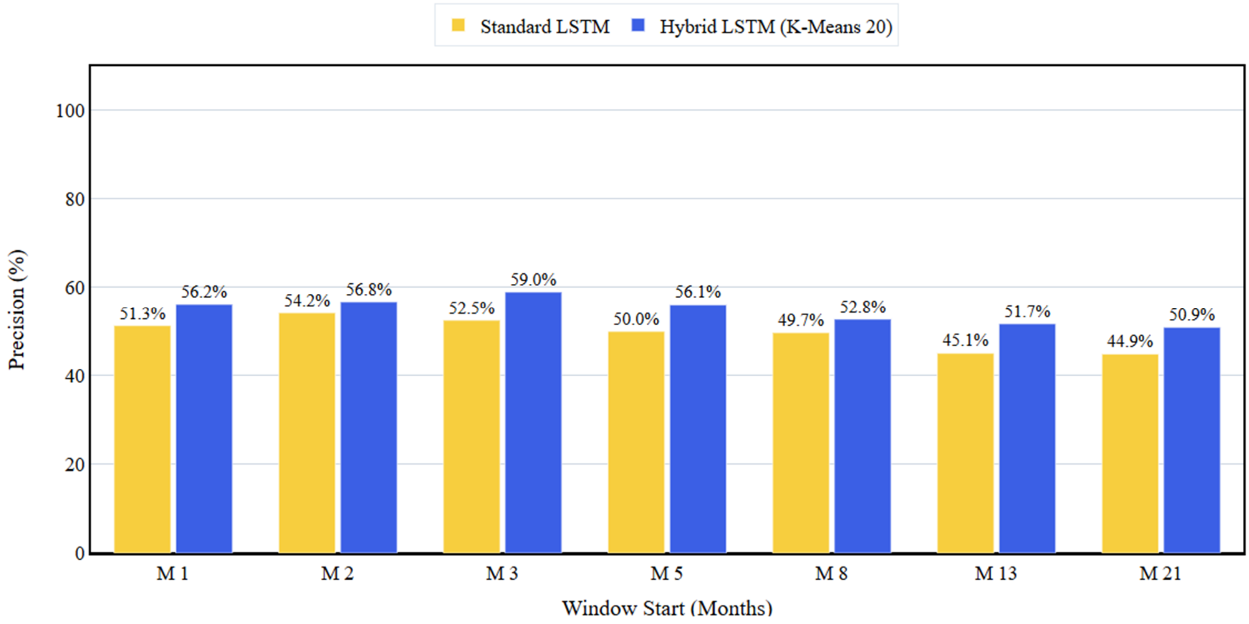

Fig. 3. Precision for standard vs hybrid LSTM modeling.

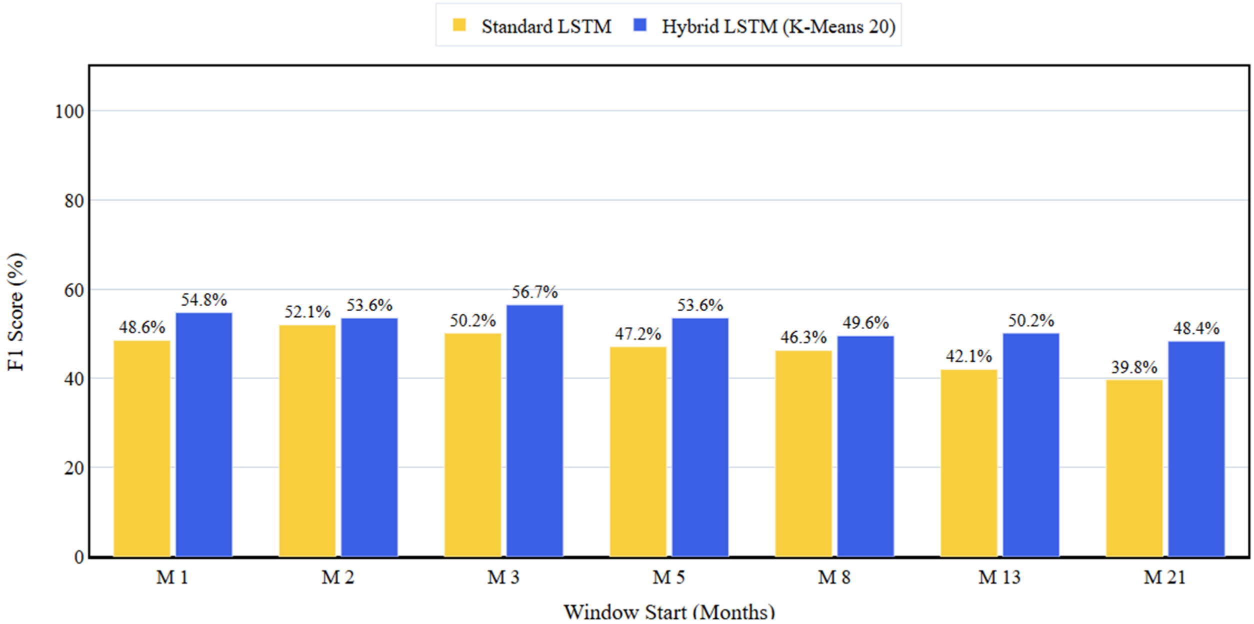

Fig. 4. F1-score for standard vs hybrid LSTM modeling.

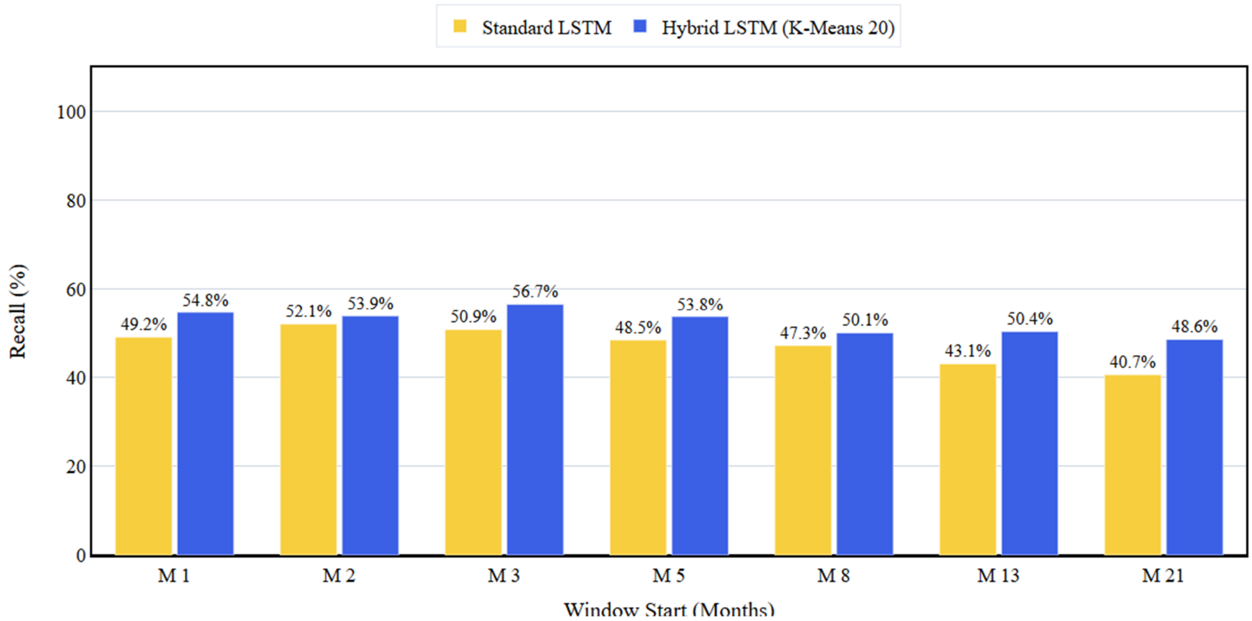

Fig. 5. Recall for standard vs hybrid LSTM modeling.

Table II presents the technical indicators and parameters, while Figures 2-5 illustrate the performance metrics (accuracy, precision, recall, and F1 score). LSTM volatility prediction (on market historical data) is used to generate the baseline performance of the supervised LSTM model. These results demonstrate LSTM's strengths and weaknesses. First, the baseline LSTM model was evaluated and compared with other supervised learners. K-means clustering was then applied to provide regime signals, which were integrated into the dataset. The classification metrics show that adding regime features improved the performance of all models. To validate this, additional non-sequential models were included to test the impact of regime features that are mathematical but are not well-suited for time-series data. The regime signaling used still improved the overall metrics of these models.

LSTM was selected as the backbone model due to its ability to capture high-risk states and its capabilities to tune to time series data. The validation was done on a walk-forward paradigm to get a better understanding of how models behave and if there are any extreme deviations in the metrics computed, as displayed in Table III. The LSTM model was implemented using TensorFlow/Keras (Sequential API) with an architecture of LSTM (32), followed by a Dropout layer (0.1) and a Dense output layer, employing 32 hidden units. The model employed the tanh activation function, 10% dropout regularization, Adam optimizer, MSE loss, training for 10 epochs with a batch size of 32, using input reshaped to (samples, 1, features), and MinMaxScaler for feature scaling.

These results demonstrate the impact of regime features on model performance. The 5-year ICICI 5-minute market data are used for computation. At each iteration, the model was trained on all available historical data up to the current month and tested on the subsequent month, yielding 60 folds across the five-year dataset. This design preserved temporal causality, avoided look-ahead bias, and provided a realistic evaluation of predictive performance under evolving market conditions.

IV. CONCLUSION

This study presented a hybrid ensemble Volatility Risk Analyzer (VRA) to address financial market volatility risk prediction issues. VRA uses the sequential modeling strength of Long Short-Term Memory (LSTM) networks and the regime detection capacity of density-based spatial clustering to balance risk forecasting accuracy, precision, and recall.

The LSTM baseline analysis proved its ability to detect all instances of high-risk volatility in the dataset with perfect recall. This feature highlights the ability of recurrent neural architectures to model financial time series with long-term relationships and nonlinear patterns. LSTM's independent ability is affected by excessive false positives, which deluge traders and risk managers with signals. The novelty of VRA lies in embedding unsupervised regime detection directly into supervised learners via one-hot encoded features, combined with a percentile-based volatility labeling strategy that prioritizes rare high-risk episodes. This integration improves recall and stability under walk-forward validation, distinguishing VRA from prior hybrid models that use clustering only as preprocessing or anomaly detection.

By clustering, K-means obtained high overall contrast, demonstrating its ability to capture structural coherence and regime stability. K-means cannot be a sufficient high risk prediction model without the ability to link clusters. The integration of these two approaches reveals the overall performance improvement. The study demonstrates that hybrid frameworks can improve financial risk prediction beyond these findings. VRA uses supervised and unsupervised paradigms for flexibility and depth. The system can dynamically adapt to changing market regimes by learning context-sensitive decision boundaries with reinforcement learning thresholds. Validating VRA across commodities, bonds, and cryptocurrencies will test its generalizability and robustness in many financial contexts. Integrating sentiment-derived signals into VRA's fusion may also help adapt precision–recall balance across regimes, complementing technical indicators. For this research, market data are readily available using broker APIs, and the same can be leveraged further.

Finally, VRA improves high-performing volatility risk prediction that is interpretable and adaptive. LSTM and K-means clusters output used as a hot encoded feature approach demonstrates the importance of financial risk procedures and may form the basis to develop financial forecasting tools further. Future research may extend and capture the behavior of multi-year time series datasets and fusion strategies, such as weighted voting and adaptive thresholds, to better balance accuracy and recall in risk prediction. The work could also incorporate imbalance-sensitive metrics such as PR AUC and undertake comparative benchmarking against other hybrid volatility models. The findings of this study will further strengthen the evaluation and contextualize the contribution of VRA.

DECLARATION OF COMPETING INTERESTS

The authors declare no competing interests.

ACKNOWLEDGMENT

Not applicable to this work.

DATA AVAILABILITY

The data used in this study were collected from [14].

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