Random Convolution Kernel–Augmented Temporal Convolutional Networks for Volatility-Dominated Financial Time Series

1st Akanksha Sharma
Maulana Azad National
Institute of Technology,
Bhopal, M.P., India
akanksha199906@gmail.com

2nd Chandan Kumar Verma
Maulana Azad National
Institute of Technology,
Bhopal, M.P., India
chandankverma@gmail.com

***Abstract*—Due to the nonstationary, noise-dominated, and nonlinear nature of volatility time series, predicting financial market volatility is challenging. Although the accuracy of forecasts has been enhanced by deep learning models in recent times, a lot of these models still depend on trainable components that are vulnerable to noise and sudden spikes in volatility. This research presents an RCK-TCN, an enhanced version of a standard TCN that incorporates fixed random convolution kernels for robust local feature extraction, to overcome these constraints. A TCN backbone models long-range temporal relationships through dilated causal convolutions, while random kernels capture short-term volatility patterns without increasing model complexity. Several equities and commodities implied volatility indexes, such as the VIX, India VIX, VXN, OVX, and GVZ, are used to assess the suggested methodology. Through the use of several error metrics, cross-validation, and SHAP-based interpretability, the experimental results show that RCK-TCN reliably produces better volatility forecasts than current deep learning baselines.**

***Index Terms*—Volatility forecasting, TCN, Random Convolutional Kernel, SHAP, Financial Time Series.**

I. Introduction

Forecasting financial market volatility is a fundamental issue in quantitative finance, with extensive applications in derivative pricing, portfolio optimisation, risk management, and regulatory monitoring. Volatility time series are notoriously difficult to forecast because they display characteristics such as clustering of volatility, sudden spikes, and regime shifts, in contrast to price or return series [1]. Because of the significant nonlinearities and noise introduced by these features, conventional forecasting methods are generally ineffective.

With their theoretical foundation in conditional heteroskedasticity, classical econometric models like ARCH and GARCH variants have been widely employed for volatility modelling [2]. However, these models can't adjust to complicated and fast-changing market situations because they use linear dynamics and limiting parametric assumptions. A growing number of financial time series are being analysed using deep learning models such as convolutional neural networks (CNNs), long short-term memories (LSTMs) [3], gated recurrent units (GRUs) [4], and hybrid CNN-RNN architectures [5]. This is because these models are able to capture nonlinear temporal patterns due to advancements in computational capacity. To forecast financial time series, Liu et al. suggested a hybrid model combining AdaBoost, KNN, and LSTM to take advantage of the synergistic benefits of recurrent networks and ensemble learning. Although these models enhance the flexibility of predictions, they have significant limitations when it comes to volatility data [5]. To incorporate data across many time scales and dynamically adjust feature selection according to market states, Li et al. presented a market-driven multi-scale time fusion model based on long short-term memories (LSTM) [6]. Recurrent architectures frequently exhibit sluggish responses to abrupt volatility shocks, while convolutional models equipped with fully trainable filters are susceptible to overfitting signals dominated by noise. The main focus of these models is on price-level prediction, not on signals driven by volatility, where the noise characteristics are very different.

Temporal Convolutional Networks (TCNs) have lately been popular for predicting time series because they use dilated causal convolutions, which make it easy to describe long-range temporal connections while keeping the sequence of events [7]. A dilated convolution in a TCN layer is defined as follows, given an input sequence x_t:

$$y_t = \sum_{k=0}^{K-1} \omega_k x_{t-dk}$$

where K is the size of the kernel, d is the dilation factor, and ω_k is the set of learnable convolution weights. To attain broad receptive fields without recurrence, TCNs stack layers with increasing dilation rates. Regardless of these benefits, the current volatility models that use TCN are dependent on learned convolutional filters, which are still vulnerable to hyperparameter selections and high-frequency noise, which are significant obstacles in time series where volatility is the dominant variable. In order to tackle issues like distributional shifts and data shortages across markets, Pan et al. developed FinWaveNet, a framework for deep volatility forecasting that incorporates residual networks, GRUs, causal and dilated

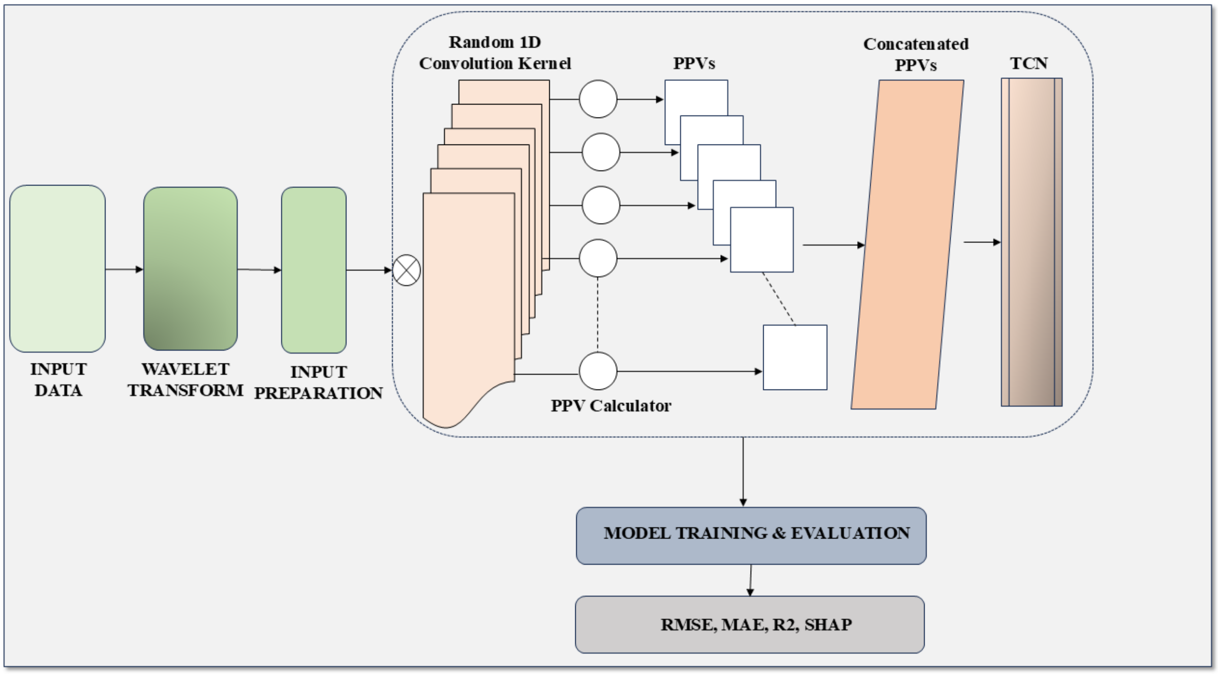

Fig. 1. Proposed Model

convolutions, and domain adaptation approaches [8]. Although these methods work well in scenarios involving several domains, they are quite complicated to implement and rely on goals for domain adaptation, which might not be relevant when there is enough volatility data from only one market. This research presents an RCK-TCN, which is an improvement on a regular TCN that uses random convolution kernels (RCKs) as a front-end feature extractor, to overcome these shortcomings as shown in Figure 1. The suggested design begins with a set of convolutional kernels that are either permanently installed or first seeded at random with the input volatility sequence. The RCK transformation for an input sequence $x \in R^{T \times F}$ is given by

$$z^{(i)} = \phi(x * k^{(i)} + b^{(i)}), i = 1, ...N,$$

where $k^{(i)}$ is the i-th random kernel, $b(i)$ is a bias term, and $\phi(.)$ is a nonlinear activation function. A variety of local patterns associated with short-term volatility variations and shock responses can be efficiently and robustly extracted from these kernels without undergoing updates during training.

A TCN backbone subsequently receives the RCK-based representations and uses stacked dilated causal convolutions and residual connections to describe long-range temporal dependencies and volatility persistence. With the addition of RCK to TCN, the suggested architecture separates temporal dependency learning from local pattern extraction, enabling each part to focus on a different facet of volatility dynamics. Since it is crucial to capture both short-term local shocks and long-term clustering behavior, this design is especially well-suited for volatility forecasting. The convolutional architecture permits parallel processing and steady gradient propagation, while the utilisation of fixed random kernels lessens the likelihood of overfitting to transient noise. The suggested model improves resilience to noise and regime shifts frequently seen in volatility series by augmenting a standard TCN instead of replacing it. This way, the strengths of temporal convolutional modelling are preserved.

The suggested model is tested on a number of implied volatility indexes for commodities and stocks, such as OVX, GVZ, VXN, and India VIX. Experimental results show that the suggested method is successful, robust, and economically relevant; these results are based on quantitative error metrics, qualitative actual-versus-predicted analysis, and SHAP-based interpretability.

The primary points of this study are as follows:

- This research presents an RCK-enhanced TCN architecture that enhances conventional TCNs by using noise-resistant random convolutional feature extraction for volatility prediction.
- Without depending on recurrent structures, a decoupled modelling framework is developed that successfully captures both short-term volatility shocks and long-range temporal relationships.
- A thorough evaluation of the empirical evidence and its interpretability is presented for several worldwide volatility indices, showing that there are continuous performance improvements and that the attribute of features is economically significant.

The subsequent sections of this paper are structured as follows. Research on financial time series and volatility forecasting is reviewed in Section II. The suggested RCK-TCN model architecture and its essential components are described in Section III. The datasets, preprocessing procedures, and experimental setup are detailed in Section IV. The quantitative evaluation, cross-validation analysis, qualitative comparisons, and interpretability assessment are all part of the empirical results, which are reported and discussed in Section V. Section VI concludes the article and provides suggestions for further study.

II. Datasets and Preprocessing

A. Datasets

The datasets used for this analysis include various implied volatility indices that stand for the stock, commodities, and safe-haven markets. The datasets utilized in this empirical financial research are all sourced from Yahoo Finance. Various market regimes, including calm times, financial stress events, and recoveries after crises, are covered by the statistics, which extend from January 2011 to December 2025. Every volatility index has its own input feature set that is built using the daily OHLC data. To round out the feature space and capture dynamics of short-term volatility, a set of technical indicators is also generated [9], [10]. These comprise the Exponential Moving Average (EMA), Simple Moving Average (SMA), Momentum (MOM), MACD, and Bollinger Bands.

TABLE I
Categorization of Volatility Datasets

Region or Market	Dataset	Description
US (Equity)	VIX	shows how volatile the S&P 500 index is likely to be
INDIA (Equity)	INDIAVIX	determines the implied volatility of the Indian equities market using options on the NIFTY index
US (Equity)	VXN	calculates the implied volatility of the NASDAQ-100 index, an indicator that is skewed toward growth-oriented and technology-focused companies
Commodity Market	OVX	stands for the implied volatility of WTI crude oil price options related to crude oil.
Commodity Market	GVZ	captures the implied volatility of gold prices.

B. Data Preprocessing

1) Wavelet Denoising: The performance of models can be negatively impacted by financial volatility time series due to their non-stationarity and the presence of high-frequency noise. Applying wavelet-based noise reduction (WNR) as a preprocessing step improves signal quality [11]. We use the discrete wavelet transform (DWT) to split the volatility series into parts with different scales, which allows us to isolate the signal from the noise-dominated high-frequency features. Reconstructing the signal using the inverse DWT is the next step after thresholding the detail coefficients to reduce noise. Various wavelet families, including Haar, Daubechies, Symlets, and Coiflets, are tested empirically in order to choose the best wavelet foundation. Coiflet 5 (coif5) outperforms the others when it comes to keeping volatility dynamics intact and successfully reducing noise. Therefore, coif5 is used in all studies.

2) Input Preparation: This study uses min-max normalization to prepare all of the input features. To avoid numerical instability during training and minimize the dominance of features with greater magnitudes, this method applies a linear transformation to scale each feature to the range [0,1]. The process of normalization is hereby defined as

$$\gamma = \frac{\gamma - \gamma_{min}}{\gamma_{max} - \gamma_{min}}$$

where the original feature value is denoted by γ. After normalization, a sliding window approach is used to make supervised learning samples from the volatility time series. In particular, the data is split into overlapping windows of the same length, and each window is regarded as a separate training sample. The input window length is set to five time steps in this work. This lets the model see how short-term volatility changes and how things group together. The next time step is used as the prediction objective for each window, which lets you predict volatility one step ahead.

III. Proposed Model

A. Problem Formulation

With d standing for the number of input characteristics, let $x_t \in R^d$ represent a multivariate volatility observation at time t. The forecasting problem is characterized as learning a nonlinear mapping, given a sliding window of length w.

$$f : [x_{t-w+1}, x_{t-w+2}, ...x_t] \longrightarrow x_{t+1}$$

given that the suggested RCK-TCN model approximatively estimates $f(.)$. To highlight dynamics of short-term volatility and recent market data, this study uses a fixed window size of $w = 5$.

B. Random Convolution Kernel Feature Extraction

A few hallmarks of the financial volatility series include regime dependence, volatility clustering, and sudden shocks. Under these circumstances, training convolutional filters using gradient-based optimization could result in unstable training and overfitting. This study solves this problem by using RCKs, which are fixed and non-trainable feature extraction mechanisms.
Assuming a window for input

$$X \in R^{w \times d},$$

Every kernel at random executes a one-dimensional convolution process that is described as

$$z_k(t) = \sum_{i=0}^{l-1} \omega_{k,i} x_{t-i}.\delta_k,$$

the $k-$th kernel's associated dilation factor is denoted by d_k, the kernel length is represented by l, and the fixed kernel weights are taken from a predetermined permutation-based distribution. With the kernel parameters held constant during training, model variance is reduced, and resistance to noisy volatility swings is enhanced [12].

We calculate the Proportion of Positive Values (PPV) statistic to get a condensed representation from the convolution output:

$$PPV_k = \frac{1}{|Z_k|}\sum_t I(z_k(t) > 0),$$

where Z_k represents the $k-$th kernel's convolution output and $I(.)$ is the indicator function. A noise-resistant and interpretable feature is produced by measuring the degree to which random kernel patterns align with local volatility changes using the PPV. A feature representation is produced by the RCK layer and is given by

$$F = [PPV_1, PPV_2, ..., PPV_k],$$

in which K is the total number of all the random convolution kernels.

C. Temporal Convolutional Network for Dependency Modeling

Despite its effectiveness in capturing local volatility patterns, the RCK layer fails to properly express temporal dependencies. In order to overcome this restriction, the RCK features that have been recovered are fed into a Temporal Convolutional Network (TCN), which excels at sequential modeling. There are a total of three 64-filter TCN backbone blocks that are layered. To prevent overly complex models, this level of detail is enough to learn hierarchical time representations. To describe fine-grained temporal transitions, which are especially important in short-horizon volatility forecasting, a kernel size of 2 is used within each block. With each TCN block, a dilated causal convolution is applied, which is

$$h^{(l)}(t) = \sum_{i=0}^{k-1} W_i^{(l)} h^{(l-1)}(t - i.d_l),$$

the size of the convolutional kernel is $k = 2$, the dilation factor at layer l is denoted by d_l, and the trainable weights are $W_i(l)$. The receptive field may efficiently increase and catch both short-term volatility shocks and longer-range dependence because the dilation factors follow an exponential growth pattern $d_l = 2^{l-1}$. For training stability and to maintain low-level temporal information, each block incorporates residual connections:

$$y^{(l)}t = \sigma(h^{(l)}(t) + y^{(l-1)}(t)),$$

where $\sigma(.)$ denotes a nonlinear activation function.

D. End-to-End RCK-TCN Architecture

Integrating temporal convolutional modeling with random kernel-based local feature extraction, the full RCK-TCN architecture provides an end-to-end framework. To begin, the RCK layer compresses the raw volatility inputs such that they only show short-term variations and local shocks. The TCN backbone then uses these traits to improve the model of volatility persistence across different time scales. The one-step-ahead volatility forecast is then generated via a fully linked regression layer:

$$\hat{x}_{t+1} = g(y^{(L)}),$$

where L is the number of TCN layers and $g(.)$ is the output mapping.

Achieving a favorable balance between robustness, expressiveness, and computing efficiency, the suggested RCK-TCN model is built by jointly constructing the architecture and hyperparameters to reflect the statistical features of volatility-dominated financial time series.

IV. Experiment and Results

A. Experimental Environment

Every experiment was executed on an NVIDIA T4 GPU (NVIDIA-SMI 535.104.05) with Python 3.10.12 and Google Colab. There is a 4:1 split of the data, with 20% set aside for validation and the rest for training. Zero imputation is used to manage missing values that arise from technical indicator calculations. Then, all features are scaled to the [0,1] range using min-max normalization. In order to train the model, input sequences of fixed length are constructed using a sliding window approach.

B. Results and Discussion

Following the completion of the model training phase, the predictive performance of the proposed RCK-TCN and all baseline models is tested on unknown test data. To give a thorough evaluation of the accuracy and robustness of the forecasts, the model is evaluated using different error measures, such as RMSE, MAE, and R^2. Model behavior is further investigated through the use of qualitative and interpretability evaluations in addition to numerical metrics.

1) Quantitative Results: The performance of the proposed RCK-TCN model was compared to several deep learning baselines on five implied volatility datasets using RMSE, MAE, and R2 metrics. The results were presented on the test sets, as shown in Table II.

With its continuously low prediction errors and high R2 values across all datasets, RCK-TCN proves to be the most effective forecasting model in terms of both accuracy and explanatory power. The RCK-TCN model outperforms the recurrent architecture and attention-based TCN models on the VIX dataset, with RMSE of 0.000199, MAE of 0.00686, and R2 score of 0.9461. India VIX and VXN show similar patterns, with RCK–TCN giving the greatest R2 values of 0.9697 and 0.9544, respectively. This shows that it works well across stock volatility indices. Using R2 values of 0.9569 on OVX and 0.9741 on GVZ, the suggested model continues to outperform in commodities markets.

A thorough examination shows that recurrent models like LSTM and GRU are good at capturing temporal relationships, but they are more vulnerable to sudden increases in volatility, which causes more inaccurate results during times of crisis. Although hybrid CNN-RNN models incorporate local feature

TABLE II
PERFORMANCE COMPARISON OF DIFFERENT MODELS ACROSS VOLATILITY DATASETS

Model	VIX			India VIX			VXN			OVX			GVZ		
	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2
CNN	0.000600	0.01360	0.8376	1.96e-04	0.01097	0.8277	4.94e-04	0.01521	0.8712	4.12e-04	0.01488	0.8893	4.06e-04	0.01419	0.9329
LSTM	0.000264	0.00867	0.9285	4.20e-05	0.00435	0.9631	1.93e-04	0.00923	0.9495	1.98e-04	0.00911	0.9416	1.62e-04	0.00886	0.9732
GRU	0.000374	0.01107	0.8987	7.15e-05	0.00596	0.9371	2.34e-04	0.01036	0.9391	2.27e-04	0.01002	0.9284	2.29e-04	0.01052	0.9622
CNN–LSTM	0.000299	0.00948	0.9191	7.78e-05	0.00595	0.9315	2.36e-04	0.01037	0.9385	2.19e-04	0.00978	0.9346	2.26e-04	0.01056	0.9626
CNN–BiLSTM	0.000445	0.01235	0.8795	9.52e-05	0.00639	0.9163	2.84e-04	0.01146	0.9260	2.58e-04	0.01121	0.9197	2.95e-04	0.01230	0.9512
CNN–GRU	0.000362	0.01015	0.9019	9.12e-05	0.00642	0.9197	2.40e-04	0.01030	0.9375	2.22e-04	0.01006	0.9318	2.66e-04	0.01117	0.9561
GRU–CNN	0.000508	0.01193	0.8624	1.31e-04	0.00806	0.8844	4.31e-04	0.01411	0.8875	3.74e-04	0.01345	0.9021	3.39e-04	0.01283	0.9440
LSTM–CNN	0.000868	0.01604	0.7647	2.51e-04	0.01168	0.7794	5.68e-04	0.01629	0.8519	4.96e-04	0.01588	0.8613	5.67e-04	0.01653	0.9064
TCN	0.000359	0.01275	0.9029	9.55e-05	0.00734	0.9159	2.53e-04	0.01036	0.9339	2.48e-04	0.01079	0.9362	4.65e-04	0.01721	0.9232
Att–TCN	0.000231	0.00833	0.9374	3.64e-05	0.00398	0.9679	2.49e-04	0.01008	0.9350	2.01e-04	0.00902	0.9478	2.27e-04	0.01037	0.9625
RCK–TCN	**0.000199**	**0.00686**	**0.9561**	**3.45e-05**	**0.00435**	**0.9697**	**1.75e-04**	**0.00876**	**0.9544**	**1.61e-04**	**0.00798**	**0.9569**	**1.57e-04**	**0.00837**	**0.9741**

TABLE III
5-FOLD CROSS-VALIDATION RESULT OF PROPOSED MODEL

Dataset \ Metrics	RMSE	MAE	R^2
VIX	0.000163	0.00531	0.9782
INDIA VIX	2.19e-05	0.00392	0.9825
VXN	0.000119	0.00549	0.9723
OVX	0.000099	0.00413	0.9895
GVZ	0.000081	0.00359	0.9917

extraction to some extent, they are nevertheless more vulnerable to noise and hyperparameter sensitivity due to their dependence on fully trainable convolutional filters. Although attention-based TCN models beat the suggested method on a consistent basis, they increase architectural complexity at the expense of performance gains over conventional TCNs.

The findings show that financial time series dominated by volatility benefit greatly from the combination of random convolution kernels and temporal convolutional networks, leading to better accuracy, stability, and generalisability in commodity and stock markets.

2) Cross-Validation and Model Robustness: All volatility datasets undergo a five-fold cross-validation (5-Fold CV) technique to evaluate the suggested RCK-TCN model's resilience and generalizability. Table III provides a summary of the average performance over all five folds based on RMSE, MAE, and R2. The results show that the suggested model is stable, with consistently good performance across all datasets, low error values, and high R2 scores. For the VIX dataset in particular, the model gets an R2 value of 0.9782, and for the VIX, OVX, and GVZ datasets in India, it does even better, with R2 values over 0.98. The model's consistent and dependable predicted performance across data divisions is further supported by the low RMSE and MAE values throughout folds.

3) Actual vs Predicted Analysis: The proposed RCK-TCN model's forecasting capability is evaluated qualitatively by presenting actual versus expected volatility charts for all five datasets: VIX, India VIX, VXN, OVX, and GVZ. Figures 2-6 shows a comparison between the suggested model's predictions and those of competing baseline models during the testing period. The RCK–TCN model shows a closer fit with the observed volatility series than alternative models across all datasets. Specifically, the suggested model excels at responding to abrupt increases and accurately tracking volatility

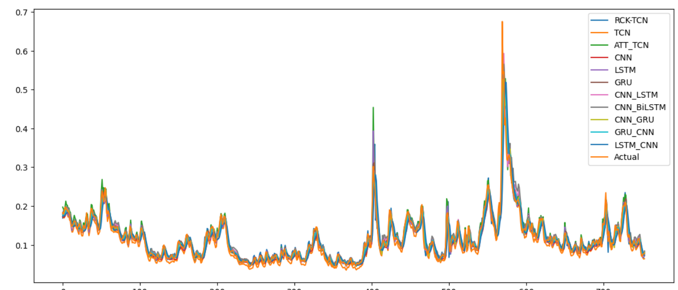

Fig. 2. Actual Vs Predicted Price Graph of VIX

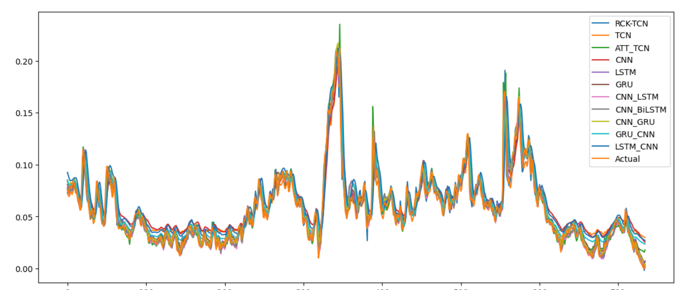

Fig. 3. Actual Vs Predicted Price Graph of INDIA VIX

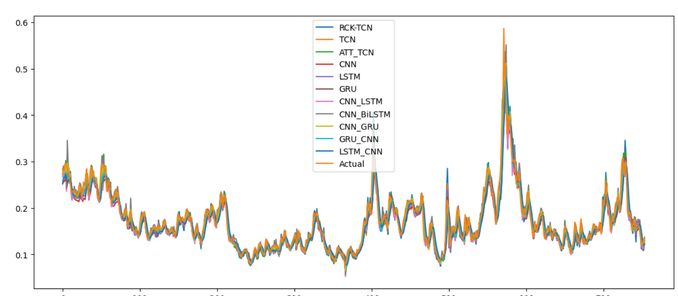

Fig. 4. Actual Vs Predicted Price Graph of VXN

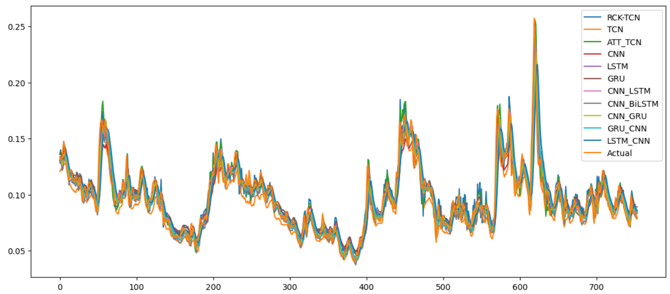

Fig. 5. Actual Vs Predicted Price Graph of OVX

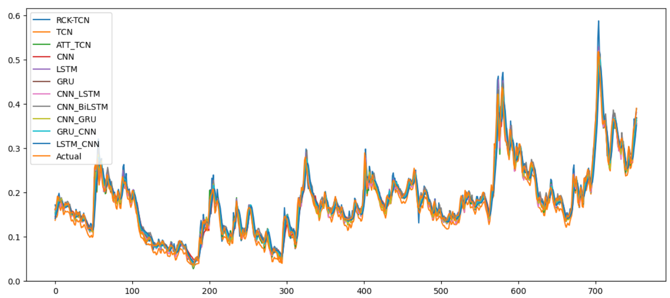

Fig. 6. Actual Vs Predicted Price Graph of GVZ

clustering, two important features of implied volatility indices. Whereas RCK-TCN more accurately captures the amplitude and timing of volatility variations, recurrent and hybrid CNN-RNN models have a tendency to smooth severe movements or show delayed responses during sudden volatility swings.

4) Interpretability via Shapley Values: To improve the interpretability of the suggested RCK–TCN model, Shapley Additive Explanations (SHAP) are used to measure how much each input attribute affects the projected volatility values. Table IV shows the average SHAP values for all input features in different volatility datasets. The results show that the relevance of features is the same in all markets. Specifically, the opening price shows the greatest SHAP contribution across all datasets, suggesting it is the most important variable for volatility

TABLE IV
AVERAGE SHAP VALUES OF INPUT FEATURES FOR DIFFERENT VOLATILITY DATASETS USING RCK-TCN

Feature	VIX	India VIX	VXN	OVX	GVZ
Open	**4.02e-03**	**1.64e-02**	**2.06e-02**	**8.50e-04**	**8.81e-03**
High	4.48e-06	4.19e-05	3.42e-05	5.99e-06	2.35e-05
Low	-3.94e-06	3.99e-05	9.59e-06	1.65e-06	4.20e-05
Close	9.46e-06	1.99e-05	1.82e-05	3.78e-06	2.58e-05
EMA	1.29e-05	1.39e-06	3.54e-05	4.05e-06	3.25e-05
SMA	-5.81e-06	3.59e-05	-2.33e-05	9.99e-06	4.47e-05
MOM	1.26e-05	2.89e-05	1.07e-05	-1.90e-06	8.63e-06
MACD	2.19e-05	1.98e-05	8.73e-06	8.91e-07	4.08e-05
SIGNAL	2.07e-05	3.41e-05	3.35e-05	2.10e-06	2.07e-05
BB Middle	2.11e-05	1.69e-05	4.29e-05	3.62e-06	1.32e-05
BB Upper	-4.73e-06	2.10e-05	1.27e-05	1.10e-05	6.49e-05
BB Lower	3.68e-06	1.79e-05	1.95e-05	2.60e-06	1.21e-05

prediction. Due to the importance of overnight data and early market mood in determining implied volatility dynamics, this discovery is in line with financial intuition.

V. Conclusion and Future Work

This research introduced an RCK–TCN model for predicting financial time series characterized by volatility. The suggested system routinely outperforms benchmark deep learning models across several volatility indices since it integrates temporal convolutional networks with random convolution kernels, which effectively capture volatility shocks and long-range relationships. Although the suggested RCK-TCN model consistently outperforms other implied volatility indices, the majority of its validations have been conducted on financial time series where volatility plays a dominant role. Due to fundamentally different dynamics, the model might not perform as well on financial data that does not include volatility, like return series or raw asset prices. Future endeavours will concentrate on enhancing the framework for multi-step volatility forecasting, integrating regime-aware mechanisms, and implementing the suggested methodology in other financial markets and higher-frequency data.

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