State-AttentNet: A Dynamic Volatility-Adaptive Hybrid Framework for Market State Classification in Frontier Economies

Md. Abul Kalam Azad[1], Abdul Kadar Muhammad Masum[2]*, Najmus Saadat[3],
Esrat Jahan[4], Ramona Birău[5], Virgil Popescu[6], Iuliana Carmen Bărbăcioru[7], Ştefan Mărgăritescu[8]
Dept. of Business and Technology Management, Islamic University of Technology, Gazipur, 1704, Bangladesh[1]
Dept. of Computer Science and Engineering, Southeast University, Dhaka, 1208, Bangladesh[2]
Computational Intelligence Lab, Southeast University, Dhaka, 1207, Bangladesh[3,4]
"Eugeniu Carada" Doctoral School of Economic Sciences, University of Craiova, Craiova, Romania[5,8]
Faculty of Economic Science, Constantin Brâncusi University of Târgu Jiu, 210185 Târgu Jiu, Romania[5]
Faculty of Economics and Business Administration, University of Craiova, Craiova, Romania[6]
Faculty of Engineering, University of Târgu Jiu, Gorj County, Romania[7]

***Abstract*—The proper identification of latent market states is important for effective risk management. However, existing frameworks are often not good at distinguishing the difference between stable situations and systemic crashes in the high entropy environments of frontier economies. To address this challenge, this study presents State-AttentNet, an application-driven market-state classification framework for the Dhaka Stock Exchange. The framework combines a volatility-adaptive labeling scheme with a bidirectional LSTM encoder and temporal attention to classify stable and crash-like market states in the Dhaka Stock Exchange. The market sensitive technical features are synthesized with Bidirectional LSTM encoder of the temporal context into a hierarchical pipeline proposed methodology. This model is also supplemented by Adaptive Temporal Attention model to bring focus to high impact volatility events in a rolling window. Here, 'crash' means an adaptive volatility-stress state, not a return direction. Empirical evaluation on a longitudinal 26-year dataset shows that the model achieves 93% classification accuracy and an AUC of 0.97. It outperforms traditional baseline models in discriminating between crash and stable states. The results have significant practical implications for institutional investors as it is a trusted, automated detection instrument. This system is conducive for state contingent risk reduction measures and minimizing false alarms in instances of correction of incidental markets. Lastly, SHAP used to check the operational integrity of the model. This suggests that structurally informative lag signals and not stochastic noise determine classification decisions.**

Keywords*—*Frontier markets; hybrid deep learning; adaptive attention mechanism; dynamic volatility labeling; Explainable AI (XAI)

I. INTRODUCTION

Financial markets are rarely in a steady state. Instead, they evolve through regimes in which expected returns, volatility and cross asset dependence change between calm, transitional and stress periods. This view is often formalized by latent states whose parameters change according to a Markov process, which makes it possible to model abrupt but persistent changes in a tractable way [1]. These regime shifts are directly relevant for risk, because correlations and volatilities are likely to increase in adverse states, which affects the diversification benefit and the cost of holding risky exposures over time [2]. Recent empirical evidence also suggests that regime detection is depends on more than just price fluctuations. It requires signals that capture the re-organization of the joint structure of the market under stress. For example, the information about realized covariance can be useful to enhance the regime identification when the standard models face difficulties, which implies that dependence dynamics should be considered as state variables in risk monitoring [3]. Regime switching specifications also enhance the realized volatility forecasting since parameters can adjust as the markets switch across volatility states [4]. At a broader macro finance scale, probabilistic models have been utilized to test the validity of bear markets and recessions occurring within a country simultaneously, reinforcing the view that regime events can have international transmissions but can largely not occur at the same time [5]. Together these studies make market state classification a fundamental task in understanding the risk in the case of non-stationarity rather than a purely descriptive task.

Building on these foundations, modern machine learning provides flexible tools for modelling nonlinear and time varying market conditions. Multi Transformer architectures have been proposed in volatility forecasting and risk assessment and have shown great potential to learn complex temporal interactions in unstable periods [6]. Hybrid machine learning designs are also highlighted for volatility prediction for risk management because the combination of complementary learners can offer superior performance compared to single learners in the context of a noisy and structurally changing environment [7]. Emerging hidden state formulations such as the Hidden Quantum Markov Model imply that richer state representations may capture aspects of regime dynamics that classical structures may not be able to express [8]. Related work also indicates that adaptive Transformer reinforcement learning frameworks can interpret sentiment-driven signals into predictive and decision oriented policies that respond to

*Corresponding author

changing market conditions [9].

In parallel, the feature space of market modeling is growing towards multimodal and explainable pipelines which are closer to the real decision setting. Temporal feature attention along with GraphSAGE on multimodal financial data shows that attention and graph encoders can learn predictive structure from interrelated sources of information [10]. Recent studies highlight explainability-guided recurrent modeling using SHAP values, demonstrating that strong performance should be accompanied by transparent reasoning under regime shifts [11]. Topology-driven CNN designs that fuse news sentiment with market dynamics are similarly suggestive of the ability of information flow and network effects to materially shape predictive behavior [12]. In high frequency situations, generative discriminative learning based on hidden state structure and discriminative boundaries has been shown to be useful in enhancing the regime separation in the situation of microstructure noise, demonstrating the importance of hybrid probabilistic and machine learning pipelines for the classification of states [13].

Despite these improvements, there remains an important gap for frontier equity markets over long horizons. Much of the recent evidence is developed market-focused, based on high frequency data sets, or assesses performance over short windows though frontier markets suffer from structural breaks and changing liquidity and participation driven shocks that may distort fixed labelling schemes and reduce the transferability of models. At the same time, theory-driven portfolio research focuses on how regimes are usually unobservable and have to be inferred with regards to filtered probabilities in order to support dynamic decision rules, which makes classification explicitly decision relevant rather than only predictive [14]. This motivates regime classifiers that can adapt labels to evolving risk and be robust under long run non stationarity and still provide interpretability for monitoring.

To overcome these limitations of the previous studies, the goal of this study is not to predict prices, but to explicitly classify the market states in Dhaka Stock Exchange using the daily data between 1999 and 2025 [15]. This study propose a dynamic volatility threshold labeling approach to the definition of stable and crash states that is adaptive to time varying market risk. The proposed framework incorporates market-sensitive technical features and propose State-AttentNet, which is a bidirectional recurrent sequence model with attention that focuses on the most informative days within each rolling window instead of all lag equally. Finally, Explainable AI (XAI) techniques are employed to ensure that the decisions of the model are not based on transient noise, but on meaningful lag signals. Experimental results demonstrate that State-AttentNet yields better classification performance compared to common recurrent baselines underscoring the use of State-AttentNet for transparent regime monitoring in a frontier market setting for risky regime aware decision making. The contribution of this study is not to introduce a fundamentally new neural architecture, but to develop an application-driven framework that integrates adaptive volatility labeling, temporal attention and explainability for long-horizon market state classification in a frontier market context.

II. Literature Review

The development of financial markets is rarely in a smooth and continuous way. Rather, emotional changes change with time, with periods of calmness punctuated by spurts of stress, volatility peaks, and dependence reversals. This set of recurring transitions has been typically described as market regimes, in which the properties of returns and risk are restructured across a set of discrete states as opposed to being due to a unique stable process. Particularly, risk management of a regime has two extensions. Regime-switching volatility models combine ARCH-type volatility clustering with latent regime changes, which enable volatility persistence to vary between regimes [16]. Less specific regime switching specifications allow the conditional distribution to differ under a Markov state process, thus allowing the mean, dispersion, and tail behavior to vary across states [17]. The volatility evidence of recent regime switching also suggests that volatility dynamics can also be regime-specific to other designs of switching between regimes that use alternative score driving designs, meaning that risk boundaries are not to be fixed as long as structural conditions change [18]. Combined, these contributions explain why the single-regime assumption may be structurally misspecified when volatility and tail risk rearrange during stress.

A first cluster of studies deals with how regime should be defined and segmented in a way that is robust, transparent and reproducible. Zegadło *et al.* [19] suggests a rule-based bull-bear dating procedure with minimum tuning, which favors label stability and the comparability between studies. Wang *et al.* [20] goes even further by adding a four-state structure through the HSMM model, demonstrating that markets may survive in intermediate conditions and that state duration characteristics enhance the validity of segmentation. Maheu *et al.* [21] similarly motivates multi-state design but focuses on real-time dating and forecasting utility as showing that regime forecasts will be particularly useful in windows of crisis since timing risk exposure is when it will matter most. Collectively these works support multi-state frameworks, however there is one limit that continues to prevail. State definitions and boundary choices are often tied to particular modelling constraints or stylization of mature market behaviour, leaving the transferability to structurally unstable markets open. A second strand reinforces regime identification by introducing forward-looking information that may adjust ahead of spot returns. Lai *et al.* [22] shows that option implied horizon spread information outperforms returns-only inputs for regime detection, supporting the concern that derivative markets contain anticipatory information on risk. However, the approach is data-intensive and assumes deep and liquid options markets. Such infrastructure is not necessarily available in frontier exchanges, diminishing feasibility at the very places where regime monitoring in a timely manner may be most important.

A third body combines probabilistic regime structure with deep learning, where state probabilities form informative inputs or scaffolding of flexible sequence models. Another regime that Erlwein-Sayer *et al.* [23] offers to deep learning template is HMM state probability extraction followed by input into an LSTM to improve his results in terms of forecasting European corporate credit spreads. Haase and Neuenkirch [24] deal with instability by combining forecasts with regime forecasts, indicating that regime forecasts enhance predictability in bull-bear regimes and returns in the US, which diminishes the vulnerability to regime specific model error. An interpretable HMM-based market situation estimator coupled with a trading strategy is created by Chen *et al.* [25] and is a useful benchmark of regime classification despite its feature design being ahead of modern representation learning. Although people demonstrate that hybridization is fruitful, the empirical evidence is largely developed market-oriented and tends to focus more on forecasting aim than on explicit daily classification of long-horizon under the changing volatility baselines.

Fourth cluster is an extension of regime forecasting to multimodal and text informed systems, indicating that market states are also determined by information diffusion and narrative shocks along with the price movement. Battazza *et al.* [26] suggests a complete end-to-end market state prediction pipeline comprising of ontology-based asset selection, non-stationary Markov chain, BERT sentiment representations, and LSTM modeling, as well as it is shown how regime inference can be incorporated into a larger allocation mechanism. The same author Mudarisov *et al.* [27] also states that LLM or FinBERT style news augmentation is better at regime prediction compared to time series pure baselines across industries, aligning with broader machine learning investigations that demonstrate the substantial impact of news sentiment on market dynamics [35]. Though promising, these methods are structurally weak in frontier settings when historical records might be biased, language diffusion might be uneven, as well as heterogeneity in news coverage can induce bias in learnt regime cues.

Recent developments have moved away the focus of prediction-focused testing to decision-focused assessment that is more in line with the trends in algorithmic trading and portfolio building in developing contexts. This fact is supported by Hanauer and Kalsbach [28] that machine learning models are capable of finding economically significant signals in a wide emerging-market equity space, which in turn makes the argument that non-linear predictability can be translated to implementable strategy value within realistic constraints. Studies that are strategy-focused also review machine learning as an engine of signals of algorithmic investment rules on both global and Central-Eastern European equity indices where technical characteristics are mapped into systematic decision regulations and measured within a consistent performance procedure [29]. In addition to equity signals at the daily-frequency, short-horizon studies of the Asian markets show how the data-driven models may be implemented into the rule-based pipelines of entry and exit decisions. The use of deep learning architectures in high-frequency pairs trading studies in Taiwan to predict the boundaries of spreads and issue trading clues supports the increased preference to use decision-relevant validation over accuracy-only prediction [30]. Collectively, these results give stronger empirical impetus to regime-sensitive targets, since algorithmic strategies are directly sensitive to volatility changes and to changes in the structure and tenacity of market regimes.

The other direction conceptualizes regimes as labels, as well as state dependent mechanisms, which change the drivers that are economically relevant. Pakštaitė *et al.* [31] demonstrates that macroeconomic influences of the Bitcoin differ across regimes with Bayesian selection HMM backbone which confirms the general suggestion that the relevance of factors can change among states. This is furthered by Wang *et al.* [32] who incorporates heteroskedastic networks with HMM and machine learning to identify regime switch and early signals, which suggests that transitions can be encoded in evolving interaction structure, as opposed to volatility. These papers reinforce the arguments in favor of adaptive, state contingent modelling but validation is still focused on individual large markets or crypto-environment, where frontier equity generalization has not been sufficiently evaluated. Shu *et al.* [33] comes up with asset specific regime labels based on jump model logic, regime forecasts based on GBDT and presents better results of dynamic allocation, which points to the importance of regime forecasts to enter portfolio policy. The use of an ensemble pipeline of machine learning and HMM with a voting classifier is suggested by Gupta *et al.* [34] and has a higher regime shift detection that is more stable and could be used to aid trading decisions in ETF-based contexts. These allocation-based evaluations are however normally carried out in developed market universes or proxy assets. They seldom treat long-horizon daily regime classification in which volatility baselines, liquidity situations, and microstructure of the market change significantly over time.

Across these studies, four gaps recur. First, long-horizon daily regime classification in the frontier equity markets is still limited, as most of the evidence is pegged to the United States or Europe, in the ETF proxies, in the options based identification or in the news rich settings. Second, there is rigidity in labelling, making the boundaries of the state in most cases fail to explicitly adjust with changes in volatility baselines that develop slowly over decades. Third, not all hybrid models are always associated with interpretability even though the regime signals are applied in risk management context where transparency is valued. Fourth, the feasibility of the data limits transfer as frontier markets seem to have only dependencies and news intensive regimes, which can be infeasible in long gaps of history.

To address these limitations, this study focuses on application-driven market-state classification in a frontier-market setting. Using 26 years of daily Dhaka Stock Exchange data [15], this study develop a causally labeled regime-classification pipeline based on a dynamic volatility-adaptive thresholding scheme. A bidirectional recurrent model with temporal attention is then applied to identify informative periods within each rolling window. Finally, this study incorporate explainability analysis to improve transparency and support decision-relevant interpretation in a data-constrained frontier-market environment.

III. Methodology

This study proposes an end-to-end deep learning architecture to classify the stable and crash market regime. As illustrated in Fig. 1, the general methodology includes data preparation, feature extraction, sequential modeling based on Bi-LSTM encoder and temporal attention mechanism and a classification head to reliably predict the final market state.

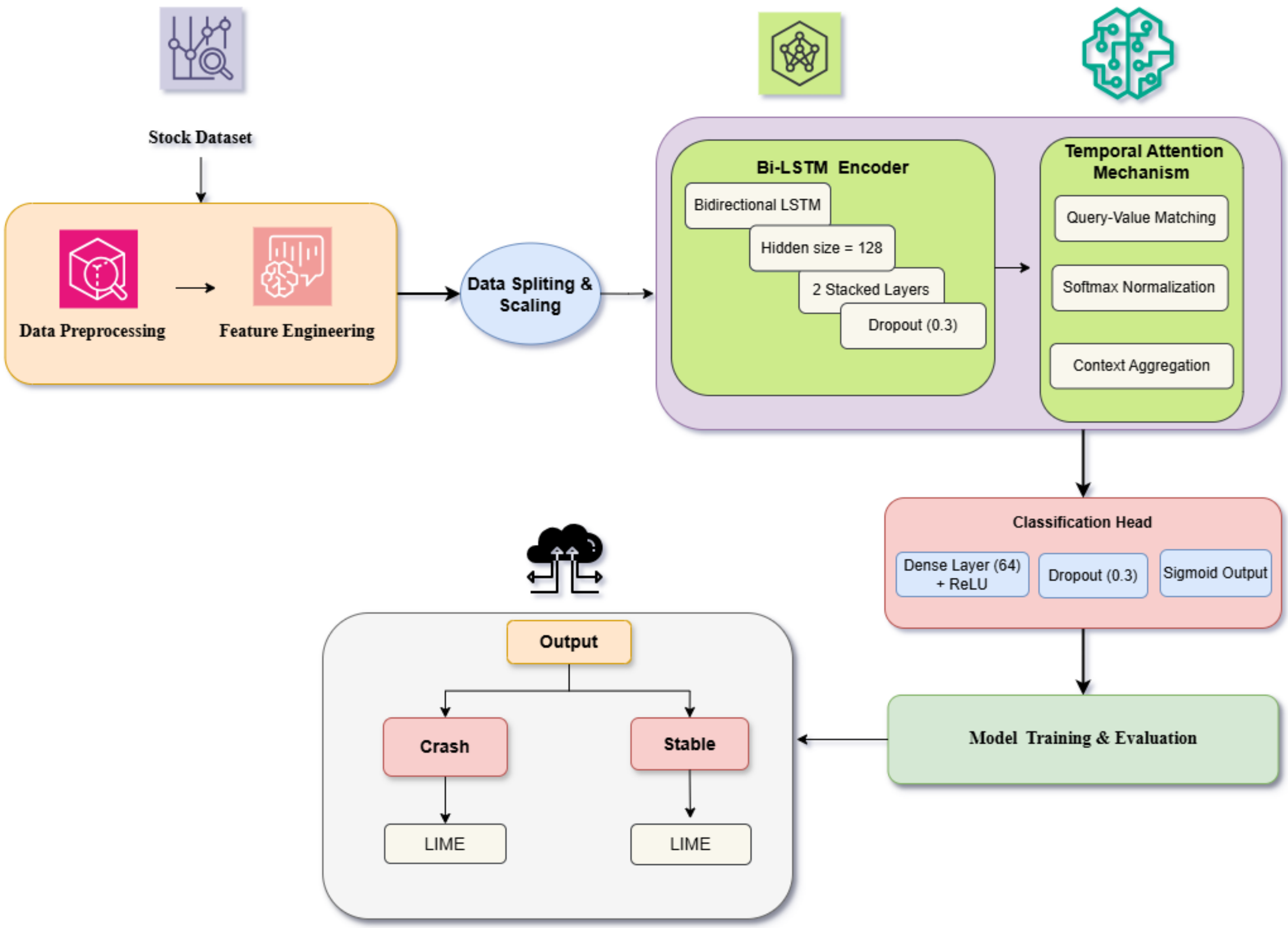

Fig. 1. End-to-end workflow of the State-AttentNet architecture.

A. Dataset Description

This study utilizes a high-fidelity dataset from the Dhaka Stock Exchange (DSE) spanning a 26-year period from 1999 to 2025. The repository contains over 1.5 million trading records across 534 distinct securities. As illustrated in Fig. 2, the market's price history exhibits extreme instability and frequent structural breaks, such as the 2010 capital market crash and the 2020 pandemic-induced volatility. Unlike developed markets, the DSE is characterized by high-entropy price movements and significant volatility clustering. These complex dynamics and heavy-tailed returns provide a rigorous benchmark for evaluating this proposed framework's ability to distinguish between systemic shocks and incidental market noise.

To empirically quantify these regime shifts, Table I presents a chronological breakdown of the distinct phases of the market that were seen within the dataset. This tabulation describes the development of volatility from the contrasting periods of systemic distress like the 2011 crash to regulatory interventions like the floor price era, thereby validating the non-stationary nature of the market. Specifically, the table calls attention to the fact that the market risk changes drastically through time. For example, the average volatility at the time of the 2011 crash was extremely high at 0.344, while in the period from 2022 to 2023 in the regulation era, volatility fell to only 0.035. This huge gap proves that the market does not act the same way every year. Because of these wide variations, a fixed-fire standard model with fixed rules would not predict the market correctly. This evidence justifies why we need a dynamic model that can automatically adapt to these changing conditions whether the market is in a bubble, a crash or a stable phase.

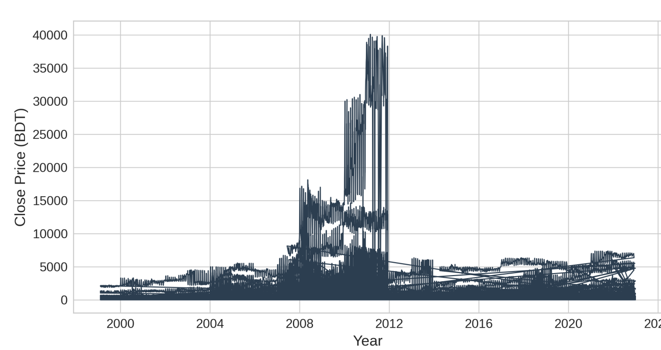

Fig. 2. Long-term price history of the DSE dataset.

TABLE I. Chronological Evolution of Market States and Volatility Dynamics (1999–2024)

Year	Market Phase	Avg. Volatility	High-Risk Days	Key Event
1999–2000	Early Development	0.097	20.9%	Initial market formation volatility.
2004	Pre-Crisis Bubble	0.155	26.1%	Early signs of market overheating.
2010	The Great Bubble	0.215	24.1%	Highest speculation period.
2011	The Crash	0.344	25.9%	Record volatility due to market collapse.
2012–2016	Stabilization	0.118	22.5%	Post-crash recovery and consolidation.
2018	Election Effect	0.102	27.1%	Uncertainty due to national elections.
2020	Pandemic Shock	0.123	25.1%	Global volatility due to COVID-19.
2022–2023	Regulation Era	0.035	16.3%	Floor Price artificially reduced volatility.
2024	Correction Phase	0.025	26.9%	Removal of floor price triggered volatility.

B. Data Preprocessing and Adaptive State Identification

The transformation of raw DSE sequences into a structured dataset involves a systematic pipeline to ensure numerical stability and contextual relevance. To maintain chronological continuity without look-ahead bias, missing values and zero-entry anomalies are addressed using the Forward Fill propagation method. Given the high-entropy nature of emerging markets, Robust Scaling is employed to normalize the feature space. This technique utilizes the median and Interquartile Range, effectively mitigating the impact of extreme price spikes while preserving significant market signals. The operation is defined, as in Eq. (1):

$$x' = \frac{x - median(x)}{IQR(x)} \tag{1}$$

The frontier markets like the DSE are usually characterized by liquidity gaps and discontinuous trading that may cause artificial breaks in observed returns. Such markets also exhibit fat-tailed returns thus Robust Scaling is the choice of scaling which would eliminate the effect of extreme shocks. A notable aspect of this framework is the departure from traditional static crash rules in favor of a Dynamic Rolling Threshold for state labeling. Let P_t denote the daily closing price and define “the log return”, as in Eq. (2):

$$r_t = \ln(P_t) - \ln(P_{t-1}) \tag{2}$$

The 20-day rolling volatility is computed as the sample standard deviation of returns over the most recent 20 trading days, as given in Eq. (3):

$$\sigma_t^{(20)} = \sqrt{\frac{1}{19}\sum_{i=0}^{19}(r_{t-i} - \overline{r_t^{(20)}})^2}, \quad \overline{r_t^{(20)}} = \frac{1}{20}\sum_{i=0}^{19} r_{t-i} \tag{3}$$

In this study, Crash refers to a volatility-spike regime rather than a return-sign definition, and, therefore, it does not necessarily imply negative returns. To adapt the crash boundary to the local volatility environment, a time-varying threshold is derived from the trailing 60-day empirical distribution of volatility. Let $Q_{0.80}(\cdot)$ denote the empirical 80th percentile. The dynamic threshold is defined, as in Eq. (4):

$$\tau_t = Q_{0.80}\left(\{\sigma_{t-j}^{(20)}\}_{j=0}^{59}\right) \tag{4}$$

The choice of the 80% percentile threshold was empirically validated to balance sensitivity to volatility spikes and robustness to noise. A sensitivity analysis was conducted using alternative thresholds (75%, 80%, and 85%), where 75% resulted in excessive false positive crash signals, while 85% reduced the model’s ability to detect meaningful volatility stress events. The 80% threshold provided the most stable and balanced performance. Market regimes are then labeled by comparing the current volatility against this adaptive threshold, as in Eq. (5):

$$\text{State}_t = \begin{cases} 1 \text{ (Crash)}, & \text{if } \sigma_t^{(20)} > \tau_t \\ 0 \text{ (Stable)}, & \text{otherwise} \end{cases} \tag{5}$$

After sorting the data by Trading_Code and Date, zero entries in Open, High, Low, Close, and Volume were treated as missing and forward-filled within each trading code to preserve temporal continuity. Observations lacking sufficient history to compute the 20-day rolling volatility, the 60-day volatility quantile used for dynamic labeling, the 14-day RSI, or the 60-day input sequence were excluded. This explains the apparent exclusion of early-period observations (e.g., 1999–2009), which do not satisfy the minimum history requirements for rolling statistics and sequence construction.

As illustrated in Fig. 3, this adaptive mechanism enables the architecture to contextually distinguish systemic structural breaks from incidental stochastic noise, as the threshold comoves with the prevailing volatility baseline rather than remaining fixed across heterogeneous market phases. For reproducibility, all rolling statistics and quantiles are computed exclusively using trailing windows within each trading code, and observations that cannot form the required rolling windows for $\sigma_t^{(20)}$ and τ_t are excluded from the final labeled sample.

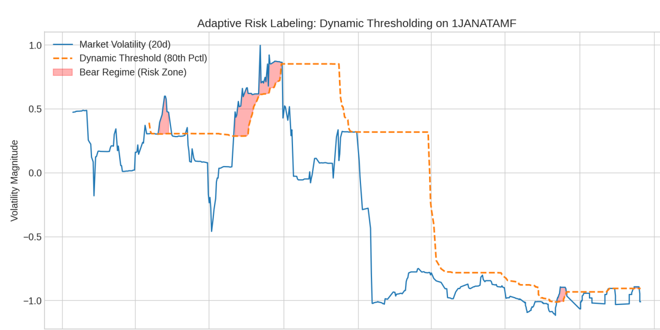

Fig. 3. Adaptive risk labeling logic using dynamic volatility thresholding.

C. Advanced Feature Engineering

To enhance the discriminative power of the proposed architecture, a multivariate feature set is constructed by capturing the temporal dynamics and liquidity shocks of the DSE. Instead of relying on raw price levels, the input vector is expanded to include indicators of momentum, volatility, and market pressure. The primary component involves the calculation of Logarithmic Returns to ensure mean-stationarity, supplemented by the Relative Strength Index and High-Low Spread to represent price dispersion. The statistical integrity and independence of this engineered feature set are validated through a correlation analysis. As shown in Fig. 4, the heatmap confirms that the selected attributes provide non-redundant information, which is essential for the model to distinguish between structural shocks and incidental market noise. Furthermore, to quantify the impact of trading activity on price movements, a composite Volume Force feature is incorporated, defined as in Eq. (6):

$$\text{Vol\_Force}_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \times \ln(\text{Volume}_t + 1) \tag{6}$$

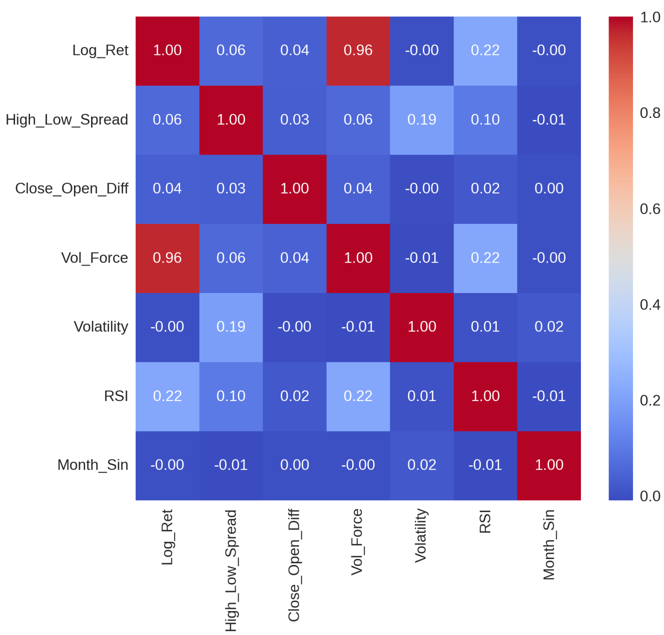

Fig. 4. Correlation matrix showcasing the statistical independence of engineered features.

To address the periodic nature of financial markets, a Cyclical Seasonality Encoding is implemented. The month index is transformed into a continuous sine-wave signal, enabling the model to recognize recurring calendar effects such as fiscal year-end adjustments without the ordinal bias inherent in raw categorical values. This temporal embedding is formally expressed, as in Eq. (7):

$$\text{Month\_Sin}_t = \sin\left(\frac{2\pi \times \text{month}}{12}\right) \tag{7}$$

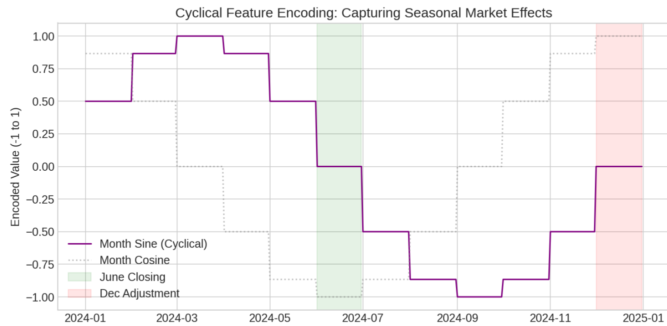

Fig. 5. Cyclical feature encoding for capturing seasonal and periodic market effects.

As illustrated in Fig. 5, this transformation effectively maps seasonal market behaviors, such as June closings and December adjustments, into a normalized periodic space. This multidimensional approach ensures that the input space captures both the geometric morphology of price trends and the underlying temporal regularities of the emerging ecosystem.

D. Proposed Model Architecture: State-AttentNet

To address the limitations of traditional sequential models, this study proposes the State-AttentNet, a hybrid architecture integrating bidirectional temporal learning with an adaptive attention mechanism. The model is specifically designed to decode market regimes by prioritizing high-impact volatility events over stochastic noise.

1) Bidirectional sequential decoding: The core of the architecture is a two-layer Bidirectional LSTM. Unlike standard recurrent units, the Bi-LSTM processes the input feature sequence $X \in \mathbb{R}^{T\times d}$ (where $T = 60$ and $d = 7$) in both forward ($\overrightarrow{h_t}$) and backward ($\overleftarrow{h_t}$) directions. This dual-stream processing allows the network to capture market patterns by analyzing both historical trends and future convergence points simultaneously. The hidden state h_t at any time step t is a concatenation of both directional vectors, as defined in Eq. (8):

$$h_t = [\overrightarrow{h_t}; \overleftarrow{h_t}] \tag{8}$$

The resulting hidden representation $H = \{h_1, h_2, ..., h_T\}$ encapsulates a robust temporal context of the market dynamics.

2) Adaptive additive temporal attention mechanism: To effectively decode market state,the model employs an additive temporal attention mechanism that dynamically prioritizes critical time steps within the 60-day lookback window.The attention score for each time step is computed, as defined in Eq. (9):

$$e_t = \mathbf{v}^\top \tanh(\mathbf{W}_h h_t + \mathbf{b}) \tag{9}$$

where, $\mathbf{W}_h$ and $\mathbf{b}$ are learnable parameters, and $\mathbf{v}$ is a trainable weight vector.

Instead of treating all historical days equally, this layer assigns a learnable scalar weight α_t to each time step, filtering out stochastic noise while highlighting high-impact volatility events. The attention scores are normalized using the softmax function, and the final context vector (c) is computed as the weighted sum of the hidden states, as defined in Eq. (10):

$$\alpha_t = \frac{\exp(e_t)}{\sum_\tau \exp(e_\tau)}, \quad c = \sum_{t=1}^{T} \alpha_t h_t \tag{10}$$

The attention mechanism assigns higher weights to time steps that are more informative for regime classification. Practically the model tends to place more emphasis on periods where volatility remains elevated for several days or where the market shows a clear drawdown pattern. Single day jumps that quickly disappear usually get lower weight. This layer is unlike normal self attention where all days are compared with each other daily but this layer assigns each day an importance score and summarizes the entire 60-day window into a single context vector.

3) Classification and output module: The aggregated context vector (c) serves as the input for the final decision-making block. It is propagated through a fully connected Dense Layer (64 units) with ReLU activation to capture non-linear feature interactions. Finally, the output is projected to a probability score using the Sigmoid activation function to classify the market state, as defined in Eq. (11):

$$\hat{y} = \sigma(W_{out} \cdot c + b_{out}) = \frac{1}{1 + e^{-(W_{out} \cdot c + b_{out})}} \tag{11}$$

If the predicted probability $\hat{y} > 0.5$, the system flags a Crash Regime; otherwise, it indicates a stable market condition.

IV. Result Analysis

A. Experimental Setup

The computational experiments were conducted within the Kaggle Notebook cloud environment, leveraging dual NVIDIA Tesla T4 GPUs to accelerate parallel tensor processing and model training. The proposed State-AttentNet architecture was implemented using the PyTorch deep learning framework, while Pandas and Scikit-learn were utilized for data preprocessing and metric evaluation. To ensure robust convergence within the non-stationary DSE environment, the network parameters were optimized using the AdamW algorithm with an initial learning rate of 0.001.

The selection of key hyperparameters was guided by validation performance and stability considerations. The hidden dimension was set to 128 to balance representational capacity and overfitting risk, as lower dimensions resulted in underfitting while higher dimensions did not yield significant improvements. The maximum number of epochs was set to 20 with early stopping based on validation loss, as the model consistently converged within this range. The threshold percentile for dynamic labeling was fixed at 80% based on empirical validation, providing a balanced trade-off between sensitivity to volatility spikes and robustness to noise. Alternative thresholds (e.g., 75% and 85%) were also evaluated but resulted in either increased false positives or reduced crash detection performance. The objective function was minimized using Binary Cross-Entropy. To maintain the structural integrity and temporal fidelity of market signals, the inherent class imbalance was addressed through the Adaptive Temporal Attention mechanism rather than external resampling. This architectural design enables the model to autonomously prioritize low-frequency, high-impact volatility features, effectively learning the dynamics of rare "Crash" regimes directly from original stochastic patterns without introducing synthetic bias. To mitigate optimization stagnation, a ReduceLROnPlateau scheduler was integrated, dynamically decaying the learning rate by a factor of 0.5 if the validation loss failed to improve for 3 consecutive epochs. The dataset was chronologically partitioned into training (2006–2021), validation (2022–2023), and testing (2024–2025) phases, approximating an 80/10/10 distribution. Unlike random shuffling, this temporal split prevents look-ahead bias by ensuring the model utilizes only historical information for training, thereby preserving the predictive integrity essential for financial time-series forecasting. The detailed hyperparameter configuration utilized in this study is summarized in Table II.

TABLE II. Hyperparameter Configuration

Hyperparameter	Value
Optimization Algorithm	AdamW
Scheduler Patience	3 Epochs (Factor=0.5)
Input Sequence (T)	60 Days
Hidden Dimensions	128 (Bi-LSTM)
Batch Size	128
Dropout Rate	0.3
Max Epochs	20

B. Evaluation of Market State Separation

The confusion matrix of State-AttentNet is presented in Fig. 6. The model demonstrates strong separation between stable and stress market regimes, with 66,772 instances correctly classified as Class 0 and 17,871 instances correctly identified as Class 1. Misclassifications remain relatively low, with 3,114 false positives (false alarms) and 3,309 false negatives (missed crash events). The overall accuracy reaches 93%, indicating reliable predictive performance.

From a risk management perspective, false negatives are particularly critical, as they correspond to periods of elevated market risk that remain undetected. The relatively low number of missed crash events suggests that the model effectively captures most volatility-stress regimes. Conversely, false positives represent unnecessary alerts, which may lead to overly conservative decisions or reduced trading activity. The controlled level of false alarms indicates that the model maintains a balanced trade-off between sensitivity and reliability.

Overall, this balance between false positives and false negatives is essential for practical deployment, where both missed risk events and excessive false alarms can have significant financial implications. Furthermore, the high F1-score and the proportional distribution of correct classifications across both classes confirm that the model's decisions are driven by structural volatility signals rather than majority class frequency, validating the efficacy of the internal attention-based weighting.

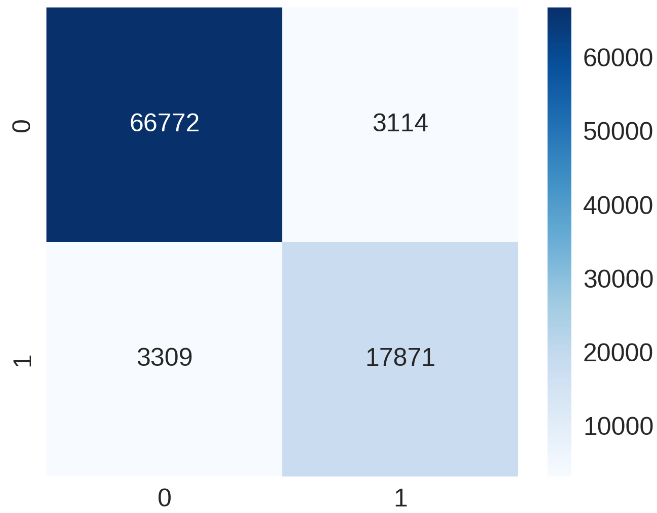

Fig. 6. Confusion matrix of the State-AttentNet model.

C. 30-Day Rolling Accuracy Over Time

Fig. 7 presents the 30-day rolling accuracy of the proposed classifier and provides a transparent view of the behavior of performance over time. The trajectory stays mostly in the upper accuracy region for long stretches indicating that the model maintains reliable state discrimination across varied phases in the market rather than getting a good score using a narrow subset of days. This persistence helps to further the credibility of the reported results because it represents consistent quality of the decision under repeated rolling evaluations. In contrast the plot also shows a limited number of short-lived accuracy drawdowns that cut across the otherwise strong pattern. Such dips are consistent with transition-heavy intervals where volatility clustering and abrupt reversals obscure regime boundaries and reduce separability of features. The rapid return to the high band indicates that the model maintains its strength and clarity once the market dynamics become stable. Operationally, these segments indicate periods when trade signals of confidence have to be handled more conservatively.

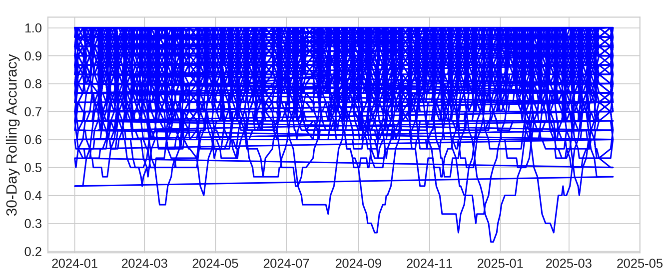

Fig. 7. Rolling accuracy across market phases.

D. ROC–AUC Performance of the State-AttentNet Model

Fig. 8 presents the ROC curve of State-AttentNet with an AUC of 0.97, which suggests high discrimination between the stable and crash regimes over a variety of decision thresholds. The curve indicates that the model is at high true-positives prior to the false-positives rate being relatively low. Interestingly, this finding is derived following a volatility based stable crash labelling framework over which regime markers are set through the rolling volatility shocks and not merely through the direction of prices. This shows how the model can be effective in learning stress-related patterns in the non-stationary and noisy dynamics of the market that can be useful in practical risk-aware regime monitoring in the DSE. A large AUC is significant in the framework of stock markets since regime decisions are threshold sensitive and trading contexts often change because of news, liquidity variations and volatility clusters. The fact that the AUC was always large indicates that the model maintains the quality of rankings of risk scores when a market condition shifts, which is critical to stable alerts and dependable decision support.

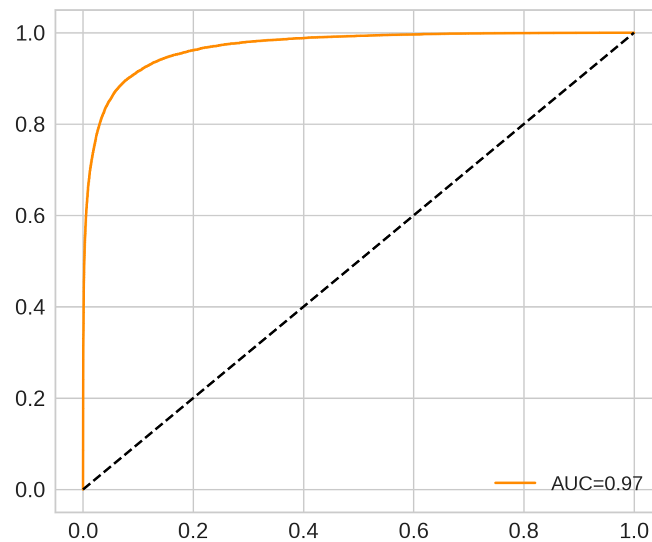

Fig. 8. ROC curve of the State-AttentNet model.

E. Comparative Performance Against Baseline Models with State-AttentNet

Table III demonstrate that State-AttentNet has the best overall performance between the compared baseline models. It attains the highest accuracy at 93.00%, exceeding LSTM with 90.64%, GRU with 91.92%, BiLSTM with 92.51%, TCN with 89.35%, and 1D-CNN with 87.41%. State-AttentNet also has the highest precision of 85.16% and the highest F1-score of 84.77, which means that it has a more balanced trade-off between crashes and false alarms. Despite BiLSTM achieving a marginally higher AUC (0.9709) compared to State-AttentNet (0.9697), the proposed framework demonstrates superior overall performance across key classification metrics. This outcome can be attributed to the temporal attention mechanism, which prioritizes minority-state awareness and enhances contextual interpretability rather than solely optimizing the ranking-based AUC metric. As a result, State-AttentNet achieves a more stable and balanced market-state classification performance, particularly in detecting volatility-driven regime shifts. By contrast, TCN and 1D-CNN have relatively poorer performances, which may indicate that convolution-based architectures are less efficient when it comes to the long-horizon regime of the DSE. On the whole, these results indicate that in the existing experimental conditions, State-AttentNet can help provide a more accurate and risk-conscious system of market state classification.

TABLE III. PERFORMANCE COMPARISON WITH BASELINE MODELS

Model	Accuracy	Precision	Recall	F1-Score	AUC
LSTM	90.64%	76.19	86.90	81.20	0.9597
GRU	91.92%	79.14	88.64	83.62	0.9683
BiLSTM	92.51%	83.05	85.17	84.10	0.9709
TCN	89.35%	75.21	79.60	77.34	0.9325
1D-CNN	87.41%	71.15	73.25	72.19	0.9055
State-AttentNet	93.00%	85.16	84.38	84.77	0.9697

The outcomes of the ablation clearly show the contribution of each architectural component in Table IV. The elimination of the attention mechanism results in a significant reduction of the performance, especially in recall and AUC, meaning that temporal weighting is very important in determining informative periods of volatility. Likewise, the deletion of bidirectional encoding decreases the model's ability to obtain both forward and backward temporal dependencies, thereby generating less stable predictions and lower overall performance. Removal of both attention and bidirectional structure is the most drastic, and this proves that the two elements work together to increase the representational ability of the model. Conversely, the full model presents the optimal balance among all the measures of evaluation and indicates that when the bidirectional sequence modeling is combined with the temporal attention that is additive, regime persistence and transitioning behavior can be learned more effectively. These results support the design decision to incorporate these elements in the suggested structure.

TABLE IV. ABLATION STUDY OF THE STATE-ATTENTNET COMPONENTS

Model Configuration	Accuracy	Precision	Recall	F1-Score	AUC
w/o Attention	0.9231	0.8559	0.8051	0.8297	0.9619
w/o Bidirectional	0.9141	0.7750	0.8888	0.8280	0.9662
w/o Attn & Bi-directional	0.9165	0.8825	0.7393	0.8046	0.9608
Full Model (State-AttentNet)	0.9300	0.8516	0.8438	0.8477	0.9697

F. Sensitivity Analysis on Lookback Window Size for State-AttentNet

We conducted a sensitivity analysis by changing the input look-back window length T of the model and measuring the impact on predictive performance of Crash to determine the reliability of the proposed State-AttentNet in a high-paced frontier-market condition. Three identical preprocessing pipeline, engineered features, data splits and training procedure were held constant across all of the runs; only the input sequence length T was varied (15, 45, and 60 days). Accuracy, Precision, Recall, F1-score and AUC are reported in Table V.

The results indicate that a lookback window of $T = 60$ provides sufficient temporal context to capture regime persistence and volatility clustering effects. Shorter windows such as $T = 15$ fail to capture extended volatility patterns, resulting in unstable predictions and significantly lower recall for crash detection. Although $T = 45$ improves performance by incorporating more temporal information, it still lacks the full context required to model sustained regime transitions. In contrast, $T = 60$ achieves the best overall performance across all evaluation metrics, suggesting an optimal balance between temporal depth and model stability. These findings demonstrate that the proposed model benefits from longer temporal dependencies and remains robust across moderate variations in the lookback window size.

TABLE V. SENSITIVITY ANALYSIS OF LOOKBACK WINDOW LENGTH

Window Size	Accuracy	Precision	Recall	F1-score	AUC
15	76.87%	80.95	61.46	69.87	0.7753
45	89.66%	75.71	79.13	77.39	0.9399
60	93.00%	85.16	84.38	84.77	0.9697

G. Analysis of Crash Signal with Price Dynamics

Fig. 9 plots the alignment of the State-AttentNet crash alert layer in responding to discontinuous instability in the price path as compared with a response to day-to-day variation. The grey line follows the stock price during 2024-2025 and the red inverted triangles indicate Crash Alert trades that will be made when the risk pattern has been identified by the model as a crash-state signature. The alerts in the early sample are focussed on the sharp decline in late October to mid-November where the price drops rapidly and rebounds with high dispersion. The second thickness cluster is observed at the late November surge and reversal zone and is a sign that extreme upside spikes and subsequent quick pullbacks are experienced by the system as crash like stress since volatility and reversal risk are co-increasing. There are repeated warnings in the last part that is of the sideways yet weak recovery which implies that the classifier is still fragile to unstable consolidation where any small movements can still constitute high downside risk. Generally, the figure proves the point in the study that State-AttentNet makes high-impact regime transitions prior and minimizes the use of stable thresholds by releasing signals primarily during structurally turbulent windows.

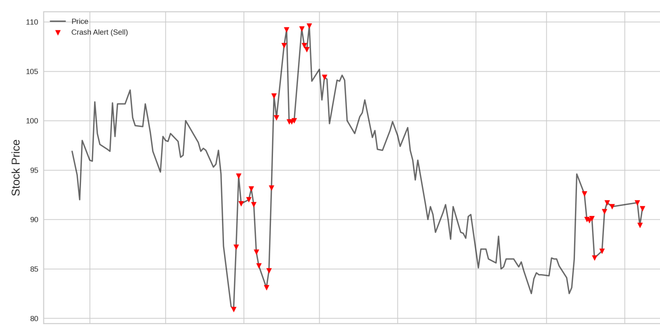

Fig. 9. Trade-signal dynamics for crash-risk (volatility-stress) control.

H. Explainability Analysis

To provide a more robust and globally interpretable explanation of the proposed framework, this study employs SHAP instead of relying on a single local surrogate explanation. The SHAP is a more stable and comprehensive measure of model behavior compared to the instance-level interpretation on a local test set, as it quantifies the contribution each instance makes to model behavior on the entire test set.

Volatility and log-return are the two features with the largest impact, as illustrated in Fig. 10 and the maximum mean absolute SHAP values of all the engineered inputs.

This means that the classifier uses mainly the market stress intensity and the dynamics of returns in differentiating between stable and crash regimes. RSI and Vol_Force make secondary contributions, which implies that regime discrimination is also supported by momentum, and trading-activity-related factors. High_Low_Spread, Close_Open_Diff, and Month_Sin, on the other hand, have relatively smaller though not dominating contributions to the prediction process, meaning that they are more complementary than dominant in the prediction process.

These results are in line with the volatility-adaptive labeling design of the research, where the volatility-related signals are supposed to be very informative. The SHAP results however also indicate that the model is not reliant on an individual feature; instead, it combines various engineered market signals in order to enhance the strength of classification. This is significant within a frontier-market environment, where structural instability and noisy price dynamics render regime identification to be sensitive to both dominant and auxiliary market indicators. A single explanation could be over-interpreted; therefore, SHAP values were summed over the entire test set. This offers a dataset-level analysis of feature relevance and minimizes the possibility of making a conclusion based on a single observation. Moreover, the SHAP ranking on the global scale is generally congruent with the analysis of temporal attention, indicating that the model focuses on informative features as well as informative time steps in detecting regime shifts.

In general, the explainability analysis using SHAP justifies the intuitive understanding that the presented framework is responding to the structurally significant market signals instead of reacting to the temporary noise. This enhances transparency and increases the practicality of the model in frontier market risk-conscious regime monitoring.

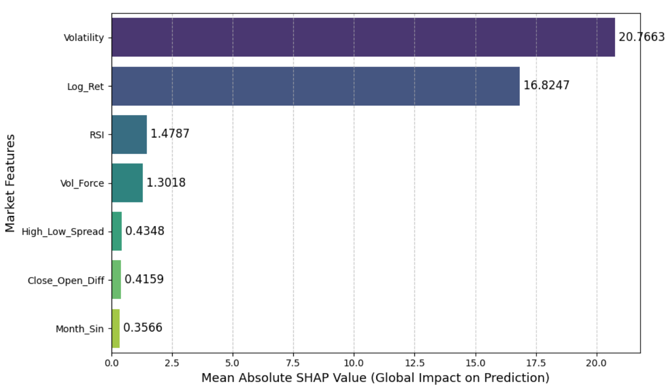

Fig. 10. Global SHAP features importance based on mean absolute SHAP values across the test set.

V. Conclusion

Financial markets are dynamic and constantly moving between stable and stress regimes, requiring the proper identification of the state to have a successful risk management process. Nevertheless, a significant proportion of literature is oriented towards developed markets or is based on predetermined labeling, which may not generalize well to frontier markets with structural volatility, changing liquidity, and time-dependent volatility patterns. In order to fill the gap, this study develops regime detection as an adaptive long-horizon classification problem and implements State-AttentNet to the Dhaka Stock Exchange based on daily data between 1999 and 2025. The framework combines the volatility-based labeling that is dynamic with market-sensitive properties, which enables the definition of stress regimes to change with the market state as opposed to using fixed thresholds.

Empirical data show that State-AttentNet attains an accuracy of 93% and AUC of 0.97, which is better than the LSTM and GRU baselines in the present experimental context. These findings indicate that attention-directed sequence modeling can be effectively used to model regime persistence and transition dynamics in non-stationary and noisy environments. Moreover, the explainability analysis reveals that the model relies on informative lag structures, which is consistent with the meaning of the model capturing meaningful regime shifts not temporary fluctuations. In general, the findings indicate that adaptive labeling combined with attention-based temporal models can offer a viable and understandable regime monitoring framework for the Dhaka Stock Exchange. A limitation of the present study is that the framework was evaluated using data from only the Dhaka Stock Exchange. In addition, class imbalance was addressed solely through the temporal attention mechanism without incorporating conventional strategies such as weighted loss functions or resampling techniques. Consequently, the responsiveness of regime signals to future market behaviour remains unobserved. During real-world implementation, regime alert-based trading decisions can impact liquidity and volatility and can also create looping effects that can change future model inputs. Further development of evaluation within live or paper trading settings will include persistence-based alerting, uncertainty-based decision rules, and controlled alert frequency to maintain stability. It is also possible to apply the framework to real-time monitoring systems with automated data pipelines and rolling retraining to continually update the system as new observations come in. The extensions are further including macroeconomic variables and also microstructure characteristics of the market and also the cross-market generalization with other frontier markets. Increasing the capacity to endure changing market conditions, future studies can incorporate drift detection algorithms to induce retraining and probability calibration methods to perceive model results as risk action measures.

Lastly, one can test the framework in a more applied context by connecting regime indicators to risk-controlling tools, and testing their performance under realistic transaction costs. The general applicability of the proposed approach can be further enhanced by extensions of the multi-class and multi-horizon regime definitions, as well as uncertainty-aware and explainable outputs.

Acknowledgment

The authors would like to express their sincere gratitude to the Southeast University, Dhaka, Bangladesh, for providing the essential laboratory facilities and technical support required to conduct this research.

References

[1] J. D. Hamilton, “A new approach to the economic analysis of nonstationary time series and the business cycle,” *Econometrica*, vol. 57, no. 2, p. 357, Feb. 1989.

[2] A. Ang and G. Bekaert, "International asset allocation with regime shifts," *Review of Financial Studies*, vol. 15, no. 4, pp. 1137–1187, Feb. 2002.

[3] A. Bucci and V. Ciciretti, "Market regime detection via realized covariances," *Econ Model*, vol. 111, p. 105832, Feb. 2022.

[4] Y. Ding, D. Kambouroudis, and D. G. McMillan, "Forecasting realised volatility using regime-switching models," *International Review of Economics & Finance*, vol. 101, p. 104171, Feb. 2025.

[5] A. Poon and D. Zhu, "Do recessions and bear markets occur concurrently across countries? A multinomial logistic approach," *Journal of Financial Econometrics*, vol. 22, no. 5, pp. 1482–1502, Feb. 2024.

[6] A. K. Mishra, J. Renganathan, and A. Gupta, "Volatility forecasting and assessing risk of financial markets using multi-transformer neural network based architecture," *Eng Appl Artif Intell*, vol. 133, p. 108223, Feb. 2024.

[7] S. Kumar, A. Rao, and M. Dhochak, "Hybrid ML models for volatility prediction in financial risk management," *International Review of Economics & Finance*, vol. 98, p. 103915, Feb. 2025.

[8] X. Song, W. Chen, and J. Lu, "Research on financial stock market prediction based on the hidden quantum markov model," *Mathematics*, vol. 13, no. 15, p. 2505, Aug. 2025.

[9] Z. Song, H. S. H. Tsang, R. T. C. Hsung, Y. Zhu, and W. L. Lo, "From market volatility to predictive insight: An adaptive transformer–RL framework for sentiment-driven financial time-series forecasting," *Forecasting*, vol. 7, no. 4, p. 55, Feb. 2025.

[10] Md. A. K. Azad *et al.*, "Stock price forecasting with temporal-feature attention and graph SAGE on multimodal financial data," in *2025 International Conference on Intelligent and Secure Engineering Solutions (CISES)*, IEEE, 2025, pp. 718–723.

[11] M. H. Begum *et al.*, "Diverse minds think alike: A SHAP-guided RNN for stock price forecasting with smart SMA optimization," in *2025 3rd International Conference on Artificial Intelligence, Blockchain, and Internet of Things (AIBThings)*, IEEE, 2025, pp. 1–5.

[12] A. K. M. Masum *et al.*, "A topology-driven CNN framework for stock price prediction using news sentiment and market dynamics," in *2025 International Conference on Intelligent and Secure Engineering Solutions (CISES)*, IEEE, 2025, pp. 712–717.

[13] A. Koukorinis, G. W. Peters, and G. Germano, "Generative-discriminative machine learning models for high-frequency financial regime classification," *Methodol Comput Appl Probab*, vol. 27, no. 2, p. 36, Feb. 2025.

[14] P. Nystrup, H. Madsen, and E. Lindström, "Dynamic portfolio optimization across hidden market regimes," *Quant Finance*, vol. 18, no. 1, pp. 83–95, Feb. 2018.

[15] M. D. A. S. Sunny, "Dhaka Stock Exchange Historical Data (1999-2025)," *Harvard Dataverse*, 2025. [Online]. Available: https://doi.org/10.7910/DVN/XIFYT1

[16] J. D. Hamilton and R. Susmel, "Autoregressive conditional heteroskedasticity and changes in regime," *J Econom*, vol. 64, no. 1–2, pp. 307–333, Feb. 1994.

[17] S. F. Gray, "Modeling the conditional distribution of interest rates as a regime-switching process," *J financ econ*, vol. 42, no. 1, pp. 27–62, Feb. 1996.

[18] S. Blazsek, D. Kong, and S. R. Shadoff, "Within-regime volatility dynamics for observable- and Markov-switching score-driven models," *Financ Res Lett*, vol. 73, p. 106631, Mar. 2025.

[19] P. Zegadło, "Identifying bull and bear market regimes with a robust rule-based method," *Res Int Bus Finance*, vol. 60, p. 101603, Feb. 2022.

[20] S. Wang, R. Gupta, and Y. J. Zhang, "Bear, bull, sidewalk, and crash: The evolution of the US stock market using over a century of daily data," *Financ Res Lett*, vol. 43, p. 101998, Feb. 2021.

[21] J. M. Maheu, T. H. McCurdy, and Y. Song, "Bull and bear markets during the COVID-19 pandemic," *Financ Res Lett*, vol. 42, p. 102091, Feb. 2021.

[22] W. N. Lai, "Detecting stock market regimes from option prices," *Operations Research Letters*, vol. 50, no. 3, pp. 260–267, Feb. 2022.

[23] C. Erlwein-Sayer, S. Grimm, A. Pieper, and R. Alsaç, "Forecasting corporate credit spreads: Regime-switching in LSTM," *Econom Stat*, Feb. 2023.

[24] F. Haase and M. Neuenkirch, "Predictability of bull and bear markets: A new look at forecasting stock market regimes (and returns) in the US," *Int J Forecast*, vol. 39, no. 2, pp. 587–605, Feb. 2023.

[25] P. Chen, D. Yi, and C. Zhao, "Trading strategy for market situation estimation based on hidden Markov model," *Mathematics*, vol. 8, no. 7, p. 1126, Feb. 2020.

[26] I. F. C. Battazza, C. M. de Oliveira Rodrigues, and J. F. L. de Oliveira, "A framework for market state prediction with ontological asset selection: A multimodal approach," *Applied Sciences*, vol. 15, no. 3, p. 1034, Feb. 2025.

[27] T. Mudarisov, R. V. State, Z. Kraussl, A. Yakubov, and T. Petrova, "Cross-sector market regime forecasting with LLM-augmented news analysis," in *Proceedings of the 5th ACM International Conference on AI in Finance*, ACM, 2024, pp. 461–468.

[28] M. X. Hanauer and T. Kalsbach, "Machine learning and the cross-section of emerging market stock returns," *Emerging Markets Review*, vol. 55, p. 101022, Jun. 2023.

[29] J. Grudniewicz and R. Ślepaczuk, "Application of machine learning in algorithmic investment strategies on global stock markets," *Res Int Bus Finance*, vol. 66, p. 102052, Oct. 2023.

[30] J. H. Liou, Y. T. Liu, and L. C. Cheng, "Price spread prediction in high-frequency pairs trading using deep learning architectures," *International Review of Financial Analysis*, vol. 96, p. 103793, Nov. 2024.

[31] V. Pakštaitė, E. Filatovas, M. Juodis, and R. Paulavičius, "Bitcoin price regime shifts: A Bayesian MCMC and hidden Markov model analysis of macroeconomic influence," *Mathematics*, vol. 13, no. 10, p. 1577, Feb. 2025.

[32] L. Wang, S. An, Z. Dong, X. Dong, and J. Li, "Early warning of regime switching in a financial time series: A heteroskedastic network model," *PLoS One*, vol. 20, no. 10, p. e0333734, Feb. 2025.

[33] Y. Shu, C. Yu, and J. M. Mulvey, "Dynamic asset allocation with asset-specific regime forecasts," *Ann Oper Res*, vol. 346, no. 1, pp. 285–318, Feb. 2025.

[34] R. Gupta, S. Kapoor, H. Gupta, and S. Natesan, "A forest of opinions: A multi-model ensemble-HMM voting framework for market regime shift detection and trading," *Data Science in Finance and Economics*, vol. 5, no. 4, pp. 466–501, 2025.

[35] M. Davidovic and J. McCleary, "News sentiment and stock market dynamics: A machine learning investigation," *Journal of Risk and Financial Management*, vol. 18, no. 8, p. 412, Feb. 2025.