From Trends to Transitions: ARIMA Powered by Hidden Markov Regimes for Adaptive Forecasting

Jyothi Badge, *Member, IAENG,* Badrikanath Praharaj, *Member, IAENG,* Dnyanesh Kavate, *Member, IAENG*

***Abstract*—This study presents an Adaptive ARIMA-HMM framework for regime-aware forecasting, applied to the Indian Sensex index. The model combines ARIMA's linear time-series prediction with probabilistic regime identification by applying Hidden Markov Models to ARIMA residuals, enabling the detection of latent market states. Using smoothed regime probabilities, it dynamically adjusts equity exposure (100%, 50%, or 0%), allowing timely responses to market shifts. In backtests, the model achieved a total return of 3040.88%, annualized return of 40.44%, Sharpe ratio of 4.63, and maximum drawdown of -19.62%, outperforming standalone ARIMA (17.12%), ARIMA-LSTM (134.09%), and static hybrid baselines (-26.65%). Sensitivity analysis confirms that a three-regime structure offers optimal balance between risk and return. While the framework improves interpretability and regime adaptation over deep learning models, its reliance on full historical data and absence of transaction cost modeling pose real-world challenges. Nonetheless, the Adaptive ARIMA-HMM offers a robust alternative to traditional and neural approaches, particularly in volatile, data-limited emerging markets, where macroeconomic regime triggers are sparse or noisy.**

***Index Terms*—ARIMA, Hidden Markov Model, Regime-Switching, Indian Stock Market, S&P BSE Sensex, Quantitative Finance**

I. Introduction

FORECASTING stock market trends is paramount in financial economics, particularly in volatile emerging markets such as India, which is characterized by structural breaks and policy-driven modifications. Linear time series models, especially the AutoRegressive Integrated Moving Average (ARIMA), are frequently employed for financial forecasting owing to their simplicity and ability to capture temporal dependencies [9]. However, these models assume constant variance and neglect the concealed regime shifts that often occur in financial time series, notably in markets susceptible to macroeconomic shocks and variations in investor sentiment.

Researchers have utilized Hidden Markov Models (HMM) to tackle this issue, offering a probabilistic framework for characterizing unobserved market states, like bull and bear phases, by analyzing observed metrics such as stock returns and volatility [10,1].These models detect regime-switching behavior and market dynamics overlooked by traditional models. In India, Hidden Markov Models (HMM) and similar Markov-switching models study volatility fluctuations [3], trading volume trends [8], and external shock effects [1].

While ARIMA models are helpful for short-term forecasting and HMM excels at revealing latent regimes, there is limited research that combines the two into a hybrid ARIMA-HMM framework, particularly in the context of the Indian stock market. International studies, including works by Palupi et al. [13] and Hu [5], demonstrate that hybrid models (like ARIMA-HMM or HMM-LSTM) can improve forecasting accuracy by incorporating regime awareness in predictions. Nonetheless, these models have not seen extensive application or validation in India, where distinct characteristics such as regulatory factors, macroeconomic policy changes, and behavioral biases demand tailored modeling strategies.

Furthermore, contemporary research on hybrid forecasting in India predominantly focuses on ARIMA-ANN or ARIMA-ML models [9,15]. Although these models proficiently capture nonlinearity, they are deficient in interpretability and the probabilistic regime-tracking capabilities provided by HMM-based methodologies. This disparity between forecasting models and regime classification techniques restricts investors' and policymakers' abilities to anticipate market turning points and adjust their strategies accordingly.

This study addresses a significant gap by introducing an Adaptive ARIMA-HMM model for regime-switching forecasting in the Indian stock market. This research makes several key contributions:

A. *Model Innovation*

We have developed an Adaptive ARIMA-HMM framework that adeptly identifies stock return patterns and transitions between regimes, improving the interpretability and accuracy of forecasts in various market conditions.

B. *Contextual Application*

This study distinguishes itself from prior research concentrated on developed markets [5,13] by implementing the hybrid model on Indian financial time series, which considers the region's unique economic structure and volatility.

C. *Empirical Validation*

This model examines data from the Indian stock index and compares its performance with ARIMA, HMM-only, and ARIMA-ANN models. The results show an impressive boost in forecast accuracy and a better grasp of regime changes.

D. *Strategic Implications*

The model is essential for investors and policymakers, providing real-time forecasts that enhance investment strategies and support well-informed decision-making.

Manuscript received July 7, 2025; revised June XX, 20XX.
Dr. Jyoti Badge is an Assistant Professor, Department of Mathematics, VIT Bhopal University, India (Email: jyoti.badge@vitbhopal.ac.in).
Mr. Badrikanath Praharaj is a student, School of Electronics and Electrical Engineering, VIT Bhopal, India (Email: badrikanath.praharaj@gmail.com).
Mr. Dnyanesh Kavate is a student, School of Computer Sciences, VIT Bhopal University, India (Email: dnyaneshkavate@gmail.com).

II. Literature Review

In emerging economies like India, financial markets often undergo exciting structural changes. These changes sometimes bring along patterns like volatility clustering and nonlinear relationships. Traditional linear models may miss these intriguing complexities, so researchers are increasingly exploring hybrid and regime-switching approaches to boost forecasting accuracy.

A. *ARIMA in Stock Forecasting*

ARIMA (AutoRegressive Integrated Moving Average) is a popular statistical method for modeling time series data, and it effectively manages linear temporal dependencies. However, it is good to know that its forecasting accuracy may take a hit in the face of volatility changes and non-stationary conditions. Many studies suggest that combining ARIMA with nonlinear or probabilistic models can effectively tackle these challenges. For instance, Kumar and Thenmozhi demonstrated how hybrid ARIMA–ANN models significantly outperformed the individual models when forecasting the NIFTY index [9]. This truly highlights the significant advantages of using hybrid approaches in financial prediction.

B. *HMM for Regime-Switching*

Hidden Markov Models (HMM) offer a robust probabilistic framework for modeling concealed states in financial time series. In India, Laha applied HMM with a Bayesian method to detect regime-switching behaviors and connected them to key economic events [10]. Similarly, Ahmad and Bandi used a Markov-switching autoregressive model to differentiate between bull and bear markets in the Indian stock market, uncovering a significant tendency for market persistence in a specific state and its sensitivity to global shocks [1]. Kumar improved regime modeling by integrating Markov-switching dynamics into a Vector Error Correction Model (MS-VECM) to analyze the long-term interactions between stock prices and trading volumes in India [8]. Additionally, Badhani used a Markov-switching ARCH framework to assess the volatility of aggregate returns, revealing two separate volatility regimes shaped by macroeconomic and global influences [3].

C. *Hybrid ARIMA-HMM Approaches*

ARIMA and HMM have distinct benefits, yet their combined use is underexplored. Palupi et al. effectively used ARIMA for price forecasting and HMM to identify bullish, bearish, and sideways financial market regimes [13]. Although it does not focus on Indian data, it offers a valuable framework for developing a hybrid ARIMA-HMM model that could benefit emerging markets.

D. *Comparative and Supporting Studies*

Ratnayaka et al. demonstrated that combining ARIMA with Artificial Neural Networks (ANN) significantly improved forecasting accuracy in the Colombo Stock Exchange [15]. This finding emphasizes the advantages of integrating linear and nonlinear models in unpredictable environments. Similarly, McDonald et al. introduced a fascinating hybrid model that blends ARIMA with a self-organizing fuzzy neural network (SOFNN) [11]. This synergy highlights the tremendous advantages of hybrid methods and demonstrates their ability to effectively capture short-term linear trends and tricky nonlinear dynamics. In Hu's 2024 research, exciting advancements were made by combining Hidden Markov Models (HMM) with Long Short-Term Memory networks (LSTM) to analyze the S&P 500 [5]. This study wonderfully illustrates how these enhanced deep learning models outperform traditional approaches. While ARIMA models and data from India were left out, the results effectively showcase the advantages of integrating temporal modeling with regime detection. Similarly, Srivastava utilized machine learning methods, including classifiers like XGBoost and Random Forest, along with macroeconomic indicators to predict Indian market regimes [17], further highlighting the importance of regime detection in boosting forecast accuracy.

Although previous studies have explored ARIMA, HMM, and other hybrid models separately or in various combinations, there has not been a direct examination of a hybrid ARIMA-HMM framework for regime-switching prediction specifically in the Indian stock market. This paper takes a friendly step forward in addressing that gap in the literature by merging ARIMA's short-term forecasting strengths with HMM's ability to identify hidden market regimes, thereby enhancing predictive understanding in a volatile and dynamic emerging market environment.

III. Research Gap

While ARIMA models are widely appreciated for time series forecasting and hidden Markov Models (HMM) are fantastic for regime-switching detection in financial markets, the hybrid ARIMA-HMM framework has not been fully explored. This is especially true in emerging markets like India, where there is so much potential.

Several key deficiencies are evident in the current literature:

A. *Limited Use of ARIMA-HMM in Indian Markets*

Although HMM effectively models regime shifts in Indian stock markets [10,1] and ARIMA is capable of forecasting stocks [9], there is a lack of significant studies that integrate ARIMA with HMM for regime-switching predictions in India. Numerous hybrid approaches concentrate on ARIMA-ANN or machine learning, highlighting a gap for probabilistic regime-sensitive models.

B. *Less Focus on Regime-Sensitive Forecasting Models*

Current models generally evaluate market behavior from a single viewpoint, neglecting structural breaks and state changes observed in volatile emerging markets. An Adaptive ARIMA-HMM can deliver forecasts that adapt according to the current market regime, a capability many traditional models lack.

C. *Neglecting Emerging Markets*

The majority of studies employing hybrid ARIMA-HMM models [13,5] primarily focus on developed markets like the S&P 500, whereas the Indian market, characterized by higher volatility, significant policy influence, and reduced informational efficiency, requires closer examination.

D. *Need for a Cohesive Method in Forecasting and Regime Identification*

In the current literature, forecasting and regime classification are often separate tasks, focusing on forecasting with ARIMA and regime identification with HMM. However, this approach could benefit from being more integrated, especially for real-time adaptable forecasting. Imagine a hybrid system where ARIMA could influence HMM or the other way around; this would lead to dynamic, regime-sensitive predictions that are more effective.

IV. Research Objectives

A. Create an Adaptive ARIMA-HMM model for forecasting the stock market in India.
B. Model the short-term dynamics of stock returns using ARIMA.
C. Identify and categorize hidden market regimes with HMM (e.g., bull, bear).
D. Incorporate ARIMA forecasts into the HMM framework for predictions that respond to dynamic regimes.
E. Evaluate the hybrid model's effectiveness against traditional ARIMA, HMM, and ARIMA-ANN models.
F. Gain insights into regime transitions and their impact on investment strategies and policy decisions.

V. Methodology

This research creates and evaluates hybrid forecasting models tailored for the Indian stock market. It integrates the Autoregressive Integrated Moving Average (ARIMA) with Hidden Markov Models (HMM) and incorporates an improved regime-aware allocation strategy. This approach aims to accurately capture both short-term linear dynamics and nonlinear structural changes in market regimes.

A. *Data Transformation*

We transformed the daily closing prices of the S&P BSE Sensex into logarithmic returns. This procedure assists in stabilizing variance and normalizing the data series, thereby enhancing the smoothness and reliability of our analysis.

$$r_t = \log\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

where:

- r_t is the log return at time t
- P_t is the current closing price of the Sensex
- P_{t-1} is the previous closing price of the Sensex

B. *ARIMA Modeling*

An ARIMA(1,0,1) model was employed to capture linear structures and short-term dependencies in the Sensex log return series. This model combines autoregressive (AR) and moving average (MA) components and assumes that the time series is stationary. The ARIMA(1,0,1) specification is defined as:

$$r_t = \mu + \phi_1 R_{t-1} + \theta_1 \epsilon_{t-1} + \epsilon_t \tag{2}$$

where:

- r_t is the log return at time t
- μ is the constant mean return
- ϕ_1 is the $\mathrm{AR}(1)$ coefficient (autoregressive term)
- θ_1 is the $\mathrm{MA}(1)$ coefficient (moving average term)
- ϵ_t is a white noise error term with $\epsilon_t \sim \mathcal{N}(0, \sigma^2)$

C. *Hidden Markov Model*

We employed a Gaussian Hidden Markov Model (HMM) comprising three states to investigate the concealed structures and dynamics within the financial time series of the Indian stock market. We established an integrated feature space by training the model with a feature set incorporating log returns and residuals from the ARIMA(1,0,1) model. This methodology allows for the identification of nonlinear temporal patterns and shifts in market behavior that linear models cannot capture. Let $\{X_t\}$ denote the observed time series, and $\{S_t\}$ be the corresponding unobserved regime sequence, where each $S_t \in \{1, 2, 3\}$. The HMM is defined by:

*1) **Initial state distribution:**:*

$$\pi_i = P(S_1 = i) \quad \text{for } i \in \{1, 2, 3\} \tag{3}$$

*2) **Transition probabilities:**:*

$$a_{ij} = P(S_{t+1} = j \mid S_t = i) \tag{4}$$

$$\sum_{j=1}^{3} a_{ij} = 1 \quad \text{for } i \in \{1, 2, 3\} \tag{5}$$

*3) **Emission densities:**:*

$$X_t \mid S_t = i \sim \mathcal{N}(\mu_i, \sigma_i^2) \tag{6}$$

Each state emits observations from a normal distribution with state-specific parameters μ_i and σ_i^2, allowing the model to distinguish between regimes based on their return distributions.

This model was trained utilizing the Baum-Welch algorithm, which functions as a maximum likelihood estimator within the Expectation-Maximization framework [14]. After this step, the Viterbi algorithm facilitated the identification of the most probable sequences of market regimes. Below is a detailed examination of the three hidden states:

- **Bull Market**: This state is characterized by a high mean and low variance, indicating stability and promising upward trends.
- **Bear Market**: This state is defined by a low or negative mean and high variance, reflecting market distress or potential crashes.
- **Sideways Market**: This state is distinguished by a near-zero mean and low variance, suggesting consolidation or low activity.

This methodology connects with the regime-switching literature in financial econometrics, showing us how market cycles are shaped by different latent states [4,6]. By understanding these regimes, we gain valuable insights that help us create trading strategies sensitive to these changes and improve our portfolio allocation.

D. *Regime-Based Allocation Strategy*

Following decoding the most probable market regimes utilizing the Hidden Markov Model (HMM), a rule-based portfolio allocation strategy was executed to synchronize equity exposure with the prevailing market conditions. The market regime for each day, Bull, Bear, or Sideways, was established using the Viterbi algorithm.

The allocation of weights was as follows:

$$w_t = \begin{cases} 1.0 & \text{if } S_t = \text{Bull} \\ 0.5 & \text{if } S_t = \text{Sideways} \\ 0.0 & \text{if } S_t = \text{Bear} \end{cases} \tag{7}$$

This framework exemplifies established practices in dynamic investing, wherein portfolio exposure is adjusted according to the market's structural phase to optimize returns and manage risk [2,7].

E. *Performance Evaluation*

To assess the effectiveness of the regime-based strategy, we computed the portfolio return at time t as:

$$R_t^p = w_t \times r_t \tag{8}$$

where:

- r_t is the log return of the Sensex at time t
- w_t is the regime-specific allocation weight at time t

We assessed model performance through these financial metrics:

- **Total Return**
  Reflects overall growth accumulated over time
- **Annualized Return**
  Represents the yearly performance compounding
- **Sharpe Ratio**
  Assesses return adjusted for risk [16]
- **Maximum Drawdown**
  Measures the largest peak-to-trough decline in portfolio value

F. *Improved ARIMA-HMM with Smoothed Allocation*

We have created an Adaptive ARIMA-HMM model to address the challenges that can arise from sudden regime changes in the discrete strategy. This model utilizes smoothed HMM posterior probabilities, allowing for a more flexible allocation mechanism.

Instead of assigning weights to just one regime, we utilized the smoothed probabilities of the regimes, $P(S_t = i \mid X_{1:T})$, and computed the portfolio weight as:

$$w_t = \sum_{i=1}^{3} P(S_t = i \mid X_{1:T}) \cdot \alpha_i \tag{9}$$

where:

- $\alpha_i \in \{0.0, 0.5, 1.0\}$ is the predefined weight for Bear, Sideways, and Bull regimes, respectively
- $P(S_t = i \mid X_{1:T})$ represents the smoothed probability of being in regime i at time t given all observations

This allocation strategy examines probabilities, allowing for finer portfolio tuning. It reduces sudden changes and lowers the risk of whipsawing, a common issue in rule-based regimes [**?**]. Additionally, it helps navigate market uncertainties for a more stable investment experience.

The return for the adaptive model becomes:

$$\text{Adaptive } R_t^p = w_t \times r_t \tag{10}$$

where w_t now dynamically reflects market confidence across regimes.

VI. Results

The results are presented compellingly and organized: Initially, we examine the descriptive statistics of log returns, elucidating the principal characteristics of the data. Subsequently, we present the notable results from the ARIMA model, illustrating its efficacy in capturing linear dependencies. After that, we dive into regime classification using a Hidden Markov Model (HMM) to identify the different states of the market. In the fourth section, we are thrilled to introduce the Hybrid ARIMA-HMM model, which combines both methodologies to enhance forecasting accuracy. We present the Adaptive Hybrid ARIMA-HMM model with a dynamic regime-based allocation for better outcomes. We also conduct a sensitivity analysis to evaluate the model's performance across various hidden state counts, ensuring a comprehensive understanding of its efficacy.

A. *Descriptive Statistics of Log Returns of S&P BSE Sensex*

TABLE I: Descriptive Statistics of Log Returns

Statistic	Value
Mean	0.000420
Std Dev	0.010536
Skewness	-1.363898
Kurtosis	20.944393
Min	-0.141017
Max	0.085947
Median	0.000631

Table 1 shows that the average daily return, indicated by the mean (0.00042), shows a slight upward trend. Daily returns vary by approximately 1%, as reflected in the standard deviation (0.0105), indicating moderate volatility. The negative skewness (-1.36) suggests losses occur more frequently than gains, while the high kurtosis value (20.94) indicates heavy tails, implying extreme returns happen more frequently than in a normal distribution. The range between minimum (-0.1410) and maximum (0.0859) values highlights the potential for significant declines alongside notable increases. The median (0.000631), being higher than the mean, reinforces that typical returns are mildly positive. These statistics collectively suggest an upward market trend accompanied by considerable downside risks and sharp fluctuations.

Figure 1 shows that despite significant disruptions, including the 2020 crash, the top-left chart reveals a strong upward

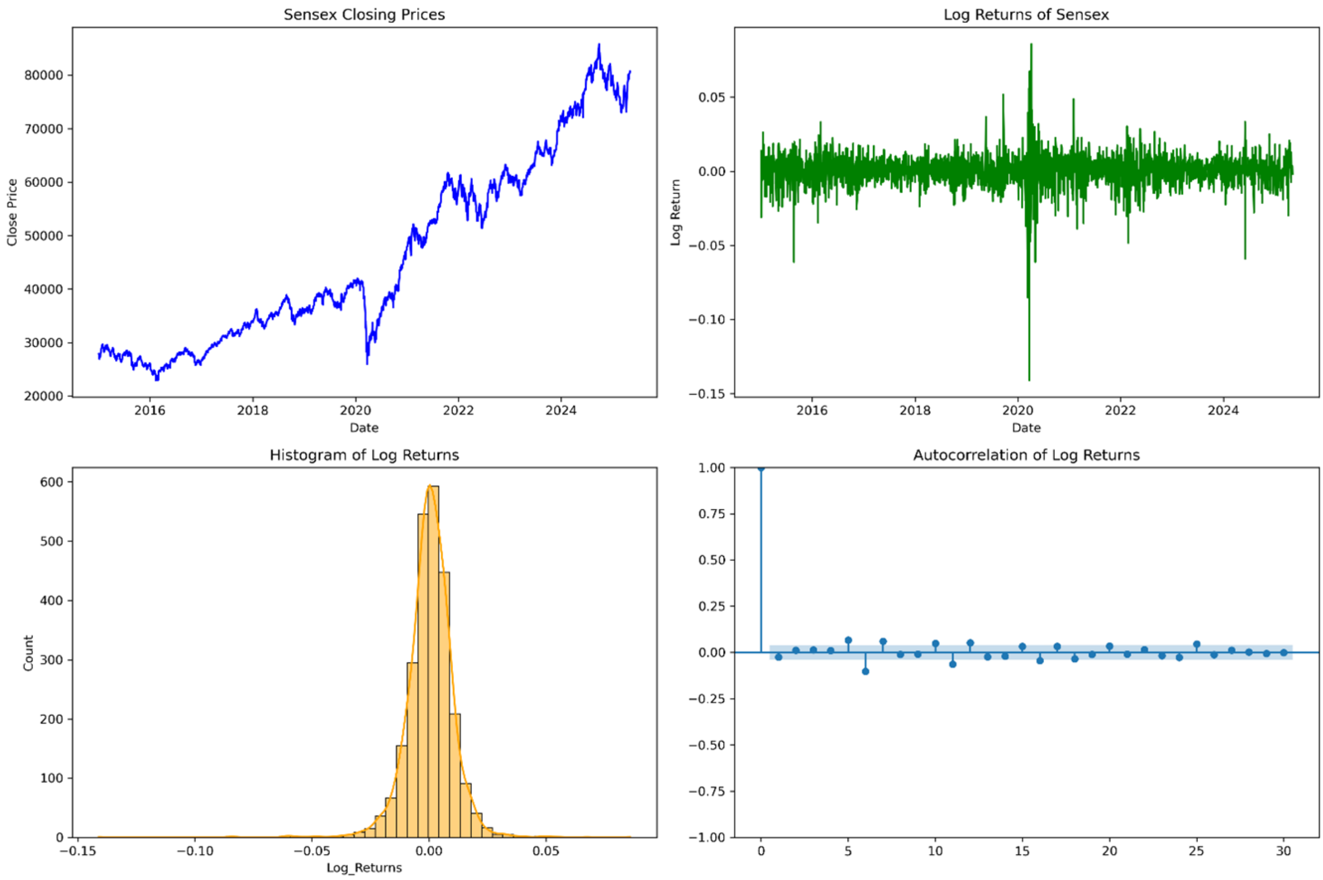

Fig. 1: Statistical Overview of Sensex Price and Return Dynamics

trend in Sensex prices. Log returns hover around zero, with occasional spikes in volatility depicted in the top-right chart. The presence of fat tails in the bottom-left histogram indicates that extreme returns happen often. Furthermore, the low autocorrelation in the bottom-right ACF chart reinforces the idea of weak-form market efficiency.

B. *ARIMA (1,0,1) Model Estimation for Sensex Log Returns*

The ARIMA(1,0,1) model shows a small but marginally significant positive mean daily return (0.0004, p=0.057). Both the AR(1) and MA(1) coefficients exhibit weak effects (-0.2256 and 0.2009 respectively) that are statistically insignificant. The model demonstrates low residual variance (0.0001), indicating good fit, though the insignificant autoregressive and moving average terms suggest limited predictability in the time series. These results point to generally random market behavior with mild positive drift.

TABLE II: ARIMA(1,0,1) Model Summary Table

Component	**Value**	**Interpretation**
Constant (Mean Return)	0.0004	Small positive value; marginally significant ($p = 0.057$).
AR(1) Coefficient	-0.2256	Weak negative autocorrelation; not significant ($p = 0.386$).
MA(1) Coefficient	0.2009	Mild moving average effect; not significant ($p = 0.447$).
Sigma² (Variance)	0.0001	Low residual variance; highly significant.

TABLE III: Diagnostic Tests for ARIMA Model

Test	**Statistic**	**p-Value**	**Conclusion**
Ljung-Box Q (Lag 1)	0.00	0.99	No residual autocorrelation; model captures serial dependence well.
Jarque-Bera (JB)	44,882.86	¡ 0.001	Strong non-normality due to negative skew and high kurtosis.
Skewness	-1.33	–	Indicates returns are left-skewed (more extreme negative returns).
Kurtosis	23.35	–	Very fat tails; presence of outliers and volatility spikes.
H Test	1.13	0.07	Mild indication of time-varying volatility; not strongly significant.

Table 3 indicates that the ARIMA model shows a slight positive average return; however, the AR and MA terms lack statistical significance, highlighting a limited autocorrelation structure in the returns. The low and significant residual variance implies the model adequately fits the data, leaving minimal unexplained variation. Table 4 presents the Ljung-Box test, which reveals no autocorrelation in the residuals, indicating a good model fit. Conversely, the Jarque-Bera test indicates significant non-normality characterized by negative skewness and high kurtosis, suggesting extreme losses and fat tails. The heteroskedasticity test indicates mild volatility clustering, although this finding is not statistically significant.

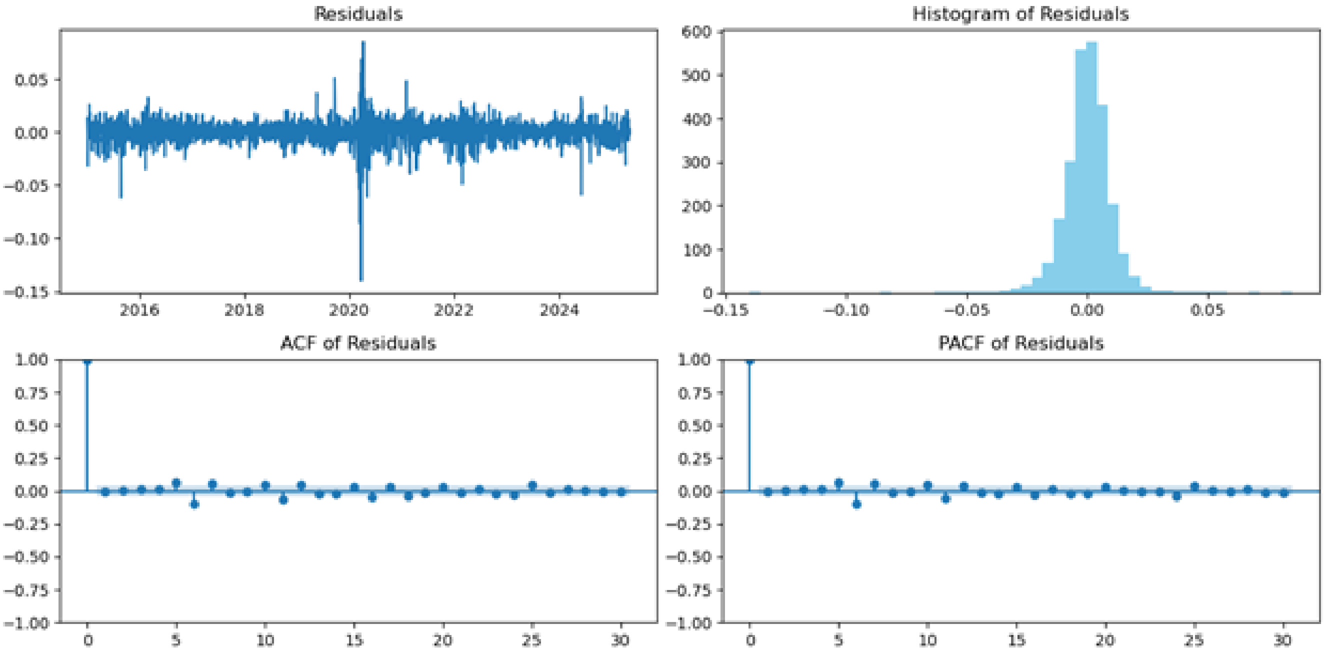

Fig. 2: Residual Diagnostics of ARIMA (1,0,1) Model

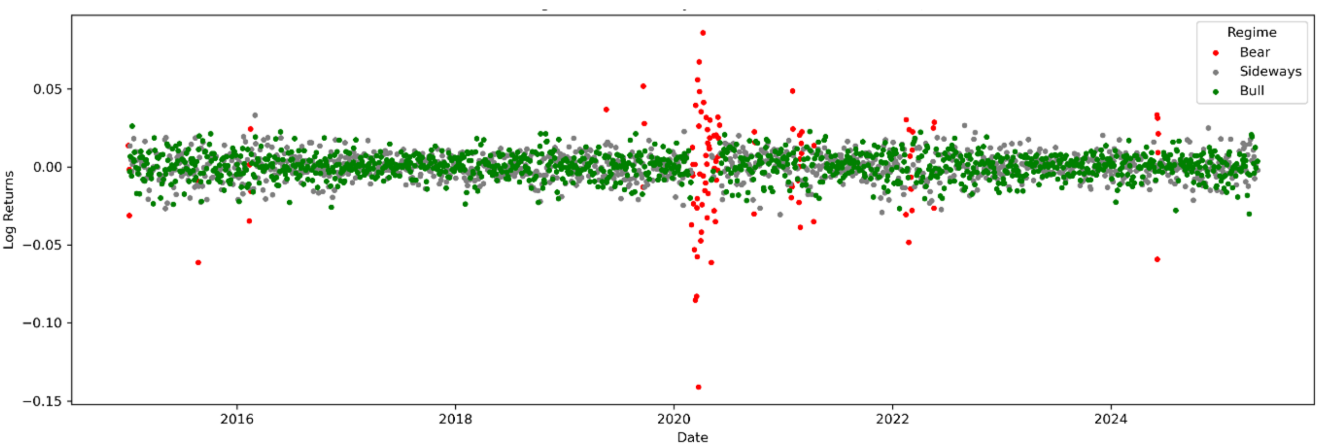

Fig. 3: Market Regimes Detected by Hidden Markov Model (HMM)

Figure 2 shows the residual diagnostics for the ARIMA (1,0,1) model, revealing a slight positive mean return without notable AR or MA effects. The residuals exhibit no autocorrelation, suggesting a fitting model. Nonetheless, there is considerable non-normality characterized by negative skewness and fat tails, along with mild but insignificant indications of heteroskedasticity.

C. Regime Identification Using Hidden Markov Model

We are thrilled to reveal concealed trends in the Sensex return dynamics. We analyze market behaviors by applying a three-state Gaussian Hidden Markov Model (HMM) to the residuals of the ARIMA(1,0,1) model. This approach offers insights into the likelihood of transitions between various market regimes, each possessing distinct attributes. We have discerned these regimes' average and volatility features, categorizing them into three phases: Bull, Sideways, and Bear markets.

Figure 3 categorizes the market into three distinct regimes: Bull, Sideways, and Bear, based on their unique return patterns. Each dot represents the prevailing regime at a specific moment, illustrating how the market has changed. These regime transitions shed light on phases of optimism, consolidation, and downturns, giving us a more precise and more comprehensive view of market behavior as it unfolds.

Figure 4 illustrates the market's confidence across different regimes over time. Rather than relying on complex classifications, it thoughtfully shows the level of dominance or uncertainty for each regime, making it easier to understand the shifts and dynamics within the market.

TABLE IV: Market Regime Distribution

Regime	**Days**	**Percentage (%)**
Bull	1,226	47.93
Sideways	1,226	47.93
Bear	106	4.14

Table 4 indicates that the Bull and Sideways regimes dom-

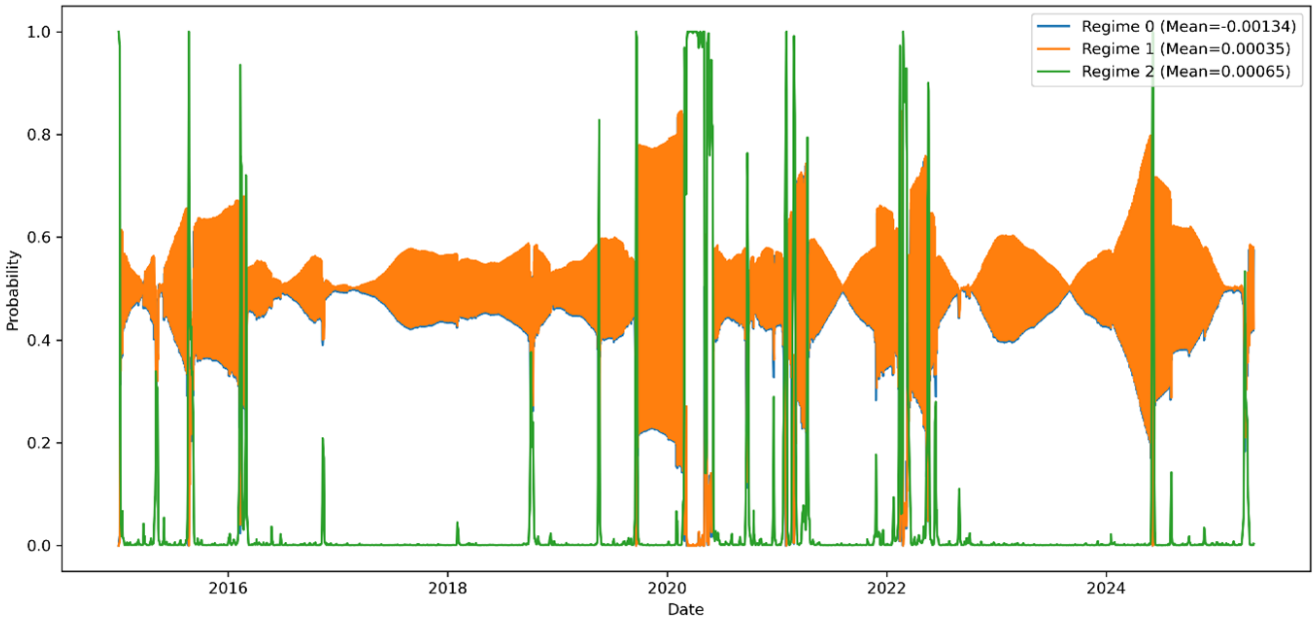

Fig. 4: Smoothed Probabilities of Market Regimes (HMM)

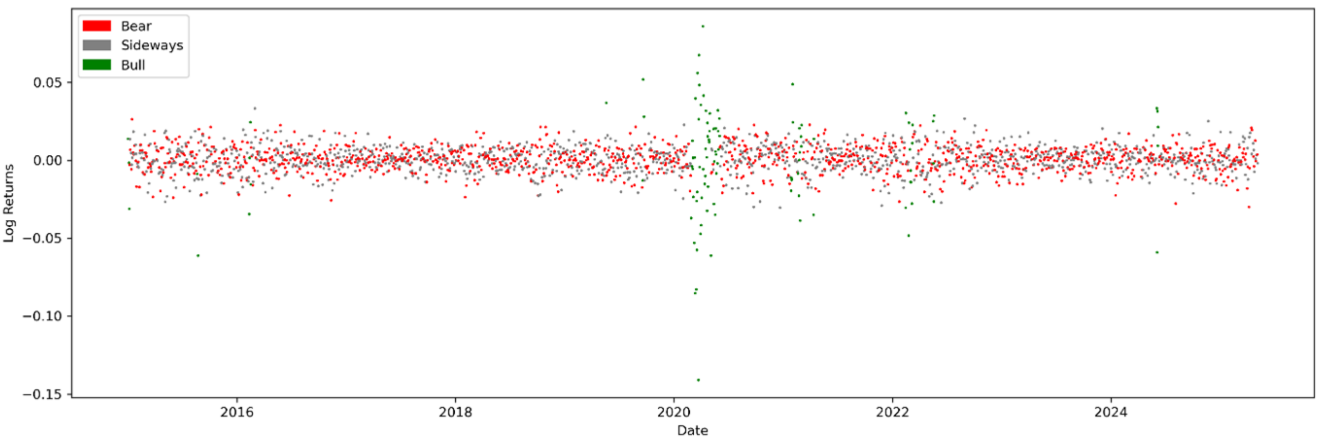

Fig. 5: Market Regimes Detected via ARIMA-HMM (on Residuals)

inate the time series, each occurring nearly 48% of the time. The Bear regime is infrequent (just over 4%), but it is typically more volatile and risky when it occurs, making it essential for risk management and strategy adjustments.

TABLE V: Regime Summary Statistics (HMM)

Regime	Mean Return	Std. Dev	Skew-ness	Kurt-osis	Days
Bear	-0.0013	0.03401	-0.77	1.96	106
Sideway	0.0003	0.00820	-0.21	0.72	1,226
Bull	0.0006	0.00806	-0.27	0.62	1,226

Table 5 illustrates that the Bear Regime has the lowest average return and the highest volatility at 3.4%. High standard deviation and negative mean signify risk-dominant conditions. Conversely, the Sideways Regime is the most stable, with a low return of 0.035% and low volatility of 0.82%. This situation usually reflects a calm or uncertain market. The Bull Regime achieves the highest average return of 0.065% with low volatility, indicating consistent and favorable trends.

TABLE VI: Transition Probability Matrix (HMM)

From → To	Bear (0)	Sideways (1)	Bull (2)
Bear	0.00	1.00	0.00
Sideways	0.989	0.00	0.011
Bull	0.142	0.00	0.858

Table 6 shows that the Bear regime regularly shifts into the Sideways regime, indicating that bear markets tend to be short-lived and recover slowly. The Sideways regime frequently transitions into Bear, suggesting it may signal impending market declines. Conversely, the Bull regime is relatively stable, with an 85.8% likelihood of remaining Bull, though it can suddenly plunge into Bear.

TABLE VII: Strategy Allocation Rules (HMM)

Regime	Equity Allocation
Bull	100% (1.0)
Sideways	50% (0.5)
Bear	0% (0.0)

Table 7 shows how the regime-based strategy tailors equity exposure according to market conditions identified by the Hidden Markov Model. It fully embraces investments during bull markets, adjusts to a 50% exposure in sideways phases, and steps back during bear markets. This thoughtful approach seeks to boost returns while keeping downside risk in check.

D. Hybrid Model ARIMA-HMM

Figure 5 illustrates that market regimes can be discerned by applying a Hidden Markov Model (HMM) to the residuals derived from the ARIMA(1,0,1) model. The data points are meticulously color-coded to signify three distinct regimes: red representing bear markets, grey indicating sideways movements, and green denoting bull markets. During bear regimes, we see higher volatility and returns that are either negative or flat. On the other hand, sideways regimes show us those neutral phases with minimal directional movements. Interestingly, we find bull regimes mainly concentrated around 2020, aligning with the post-crash recovery and highlighting those brief yet intense upward movements. This precise segmentation confirms the HMM's ability to uncover hidden market structures that might not be visible in the raw returns alone.

TABLE VIII: Regime Frequency Table by ARIMA-HMM

Regime	Days	Percentage
Bear	1,227	47.97%
Sideways	1,227	47.97%
Bull	104	4.07%

Table 8 shows that while the Bull regime is rare, it tends to be quite unpredictable when it does occur. In contrast, the Bear and Sideways regimes seem to receive nearly equal attention, suggesting that we often find ourselves in risk-neutral or flat-market scenarios. The regime labels were likely chosen based on volatility rather than the direction of returns.

TABLE IX: ARIMA-HMM Regime Summary Table

Regime	Mean	Std. Dev	Skewness	Kurtosis	Days
Bear	0.00026	0.00809	-0.27	0.61	1,227
Sideways	-0.00010	0.00827	-0.24	0.78	1,227
Bull	-0.00176	0.03402	-0.75	1.90	104

Table 9 shows the Bull regime is the most volatile, with left-skewed, fat-tailed residuals, highlighting significant downside risk that may seem surprising given the "Bull" label, which is misleading based on volatility ordering. On the other hand, the Bear and Sideways regimes display low volatility and quite similar statistical profiles, although they have slightly positive and negative residual means, respectively. Interestingly, all regimes' residuals reveal non-normality, a characteristic we typically expect in financial time series.

TABLE X: Transition Probability Matrix by ARIMA-HMM

From $\rightarrow$ To	Bear	Sideways	Bull
Bear	0.00	1.00	0.00
Sideways	0.99	0.00	0.01
Bull	0.14	0.00	0.86

Table 10 shows that the Bear regime shifts smoothly into the Sideways condition, rarely remaining in the Bear phase for long or abruptly moving to the Bull phase. This indicates that bear periods are usually brief and lead to a consolidation phase. Interestingly, the Sideways regime often appears before the Bear phase, as a helpful indicator for potential downturns. Although the Bull phase tends to remain stable, it can shift into the Bear phase but does not move directly to the Sideways condition.

E. Performance Comparison of ARIMA, HMM, and ARIMA-HMM

TABLE XI: Comparative Analysis with Traditional Models

Model	Tot Return	Ann Return	Sharpe	Drawdown
ARIMA	141.41%	9.09%	0.56	-38.34%
HMM	-27.30%	-3.10%	-0.31	-38.81%
A-HMM	-26.65%	-3.01%	-0.32	-37.00%

Table 11 illustrates that the comparative analysis of the baseline models emphasizes both the advantages and shortcomings of traditional approaches. The ARIMA(1,0,1) model captures short-term linear dependencies, yielding a total return of 141.41% and an annualized return of 9.09%, with a Sharpe ratio 0.56. Its sensitivity to economic downturns is apparent, marked by a maximum drawdown of 38.34%. The pure Hidden Markov Model (HMM) reveals hidden market structures but struggles to convert regime identification into profits, resulting in a total return of 27.30% and a Sharpe ratio 0.31. The hybrid ARIMA-HMM model also underperformed (26.65% total return) and did not improve drawdown risk (37.00%), showing that a simple integration of these models is inadequate for real-time market adaptation. These findings underscore a key limitation: while regime information is valuable, its utility depends on how effectively it is incorporated into decision-making. In response, we introduce an **Adaptive ARIMA-HMM model**, a refined approach that leverages smoothed regime probabilities to adjust asset allocations dynamically. By enhancing responsiveness to market shifts and optimizing exposure across regimes, this model aims to improve return potential and risk management, overcoming the rigidity of earlier frameworks.

F. Adaptive ARIMA-HMM

The Adaptive ARIMA-HMM brings some exciting improvements to boost accuracy and risk management.

*1) **Smoothed Probabilities**:* Instead of relying on fixed regime labels, it uses the HMM's smoothed probabilities for weighted allocations across regimes, which helps create smoother transitions.

*2) **Dynamic Allocation**:* Based on our confidence in the regime, equity exposure is adjusted dynamically, 100% in bull markets, 50% during sideways movements, and 0% in bear phases. This approach minimizes overreactions to short-term fluctuations.

*3) **Residual-Based Modeling**:* The Hidden Markov Model (HMM) is employed on the residuals of the Autoregressive Integrated Moving Average (ARIMA) instead of the raw returns, thereby enabling the identification of concealed patterns and the enhancement of regime detection.

*4) **Improved Performance**:* These modifications greatly enhance the stability of returns, increase the Sharpe ratio, and reduce drawdown, rendering the model more responsive to actual market conditions.

TABLE XII: Regime Summary – Adaptive ARIMA-HMM

R	Description	Mean	Std	Skew	Kurt	Days
0	Stable	0.0000	0.0073	0.01	0.68	1,229
1	Bear	-0.0003	0.0073	0.13	0.50	1,229
2	Bull	0.0028	0.0308	-0.25	1.06	100

Table 12 shows us that Regime 0 (Sideways) has a mean residual of just 0.00003 and a low standard deviation of 0.0073, which suggests there is not much movement and that volatility is relatively low. We see a stable, flat market with nearly zero skewness and moderate kurtosis. This regime represents our longest data share at 1,229 days, showcasing extensive consolidation periods. On the other hand, Regime 1 (Bear) presents a slightly negative mean residual of 0.00026, with volatility comparable to that of Regime 0. Additionally, the skewness in this case is somewhat positive, although the return profile stays flat to mildly negative. This regime spans 1,229 days, likely overlapping with the sideways conditions because of these comparable statistics. Regime 2 (Bull) shows a strong positive mean residual (0.00276) and high volatility (0.0308), indicative of rapidly rising markets. The negative skewness and high kurtosis indicate notable positive returns with occasional sharp pullbacks. This regime is less common, lasting only 100 days, but it generates significant bullish phases.

TABLE XIII: Regime Summary Statistics (ARIMA-HMM)

R	Description	Mean	Std	Skew	Kurt	Days
0	Stable	0.0000	0.0073	0.01	0.68	1,229
1	Bear	-0.0003	0.0073	0.13	0.50	1,229
2	Bull	0.0028	0.0308	-0.25	1.06	100

Table 13 shows the transition probability matrix and highlights the chances of market shifts across different regimes. Notably, Regime 0 (Sideways) has an extremely high 99.9% probability of moving to Regime 1 (Bear), suggesting that downturns often follow periods of stagnation. Interestingly, Regime 1 flips back to Regime 0 approximately 97.9% of the time, indicating a cycling pattern between bearish and neutral phases. Conversely, Regime 2 (Bull) stands out as the most stable, with an impressive 86.2% chance of continuation. This illustrates how effectively the model captures bullish market momentum and trends.

TABLE XIV: Model Performance Comparison

Model	Tot Ret (%)	Ann Ret (%)	Sharpe	MD (%)
ARIMA	141.41	9.09	0.56	−38.34
HMM	−27.30	−3.10	−0.31	−38.81
A-HMM	−26.65	−3.01	−0.32	−37.00
A-ANN	134.09	8.76	0.73	−28.95
AAHMM	3040.88	40.44	4.63	−19.62

Table 14 provides a delightful comparison of various forecasting models in the Indian stock market. The ARIMA model impresses with a total return of 141.41% and a Sharpe ratio 0.56. However, it does have a maximum drawdown of 38.34%, which suggests some noteworthy downside risk. Meanwhile, the HMM model excels in detecting regimes, making it quite valuable; unfortunately, it falls short in returns, showing a decrease of 27.30% and a negative Sharpe ratio of 0.31, which may make it less ideal for forecasting purposes. The basic ARIMA-HMM hybrid also underperforms, with a negative return of 26.65% and a high drawdown of 37.00%. On the other hand, the ARIMA-ANN model demonstrates promising results, achieving a substantial total return of 134.09%, an annual return of 8.76%, and a higher Sharpe ratio of 0.73 in comparison to ARIMA, while lowering the drawdown to 28.95%. In contrast, the Adaptive ARIMA-HMM model reports an exceptional total return of 3040.88%, an annual return of 40.44%, and a Sharpe ratio of 4.63, while reducing drawdown to 19.62%.

Figure 6 demonstrates that the comparative bar charts effectively showcase the superior performance of the Improved ARIMA-HMM model across all essential evaluation metrics. Regarding profitability, it secures an impressive total return of over 3000% and an annual return exceeding 40%, significantly outpacing all other models, such as ARIMA, HMM, ARIMA-HMM, and ARIMA-ANN. the Sharpe ratio of 4.63 indicates that this model provides exceptional risk-adjusted performance, distinguishing itself significantly from other models with ratios below 1.0. Furthermore, the Enhanced ARIMA-HMM demonstrates the lowest maximum drawdown at 19.62%, illustrating its noteworthy capability to endure market declines. Other models experience over 37% drawdowns, increasing susceptibility to market fluctuations. This visualization shows that the ARIMA-HMM framework improves returns and enhances stability and drawdown management, making it the most effective model evaluated.

G. *Sensitivity analysis*

To fully appreciate the enhanced ARIMA-HMM model's efficacy, a sensitivity analysis was conducted by varying the number of hidden states within the hidden Markov Model (HMM) from 2 to 5. The objective was to investigate the impact of modifying the complexity of the model on key performance metrics, including total return, annual return, Sharpe ratio, and maximum drawdown.

TABLE XV: Sensitivity Analysis of Adaptive ARIMA-HMM with Varying Hidden States

H States	Tot Ret (%)	Ann Ret (%)	Sharpe	Max DD (%)
2	97.11	6.91	1.29	−8.57
3	3040.88	40.44	4.63	−19.62
4	5803.82	49.45	4.44	−18.39
5	3651.01	42.91	3.57	−20.34

Table 15 presents insights derived from our sensitivity analysis, which is notably intriguing. The results indicate a trend: utilizing a 2-state model yields relatively modest returns, specifically a total return of 6.91% and an annual return of 6.91%, alongside a slight drawdown of-8.57%. A three-state model can significantly enhance risk-adjusted performance, yielding an impressive Sharpe ratio of 4.63 and a total return of 3040.88%. The four-state model advances

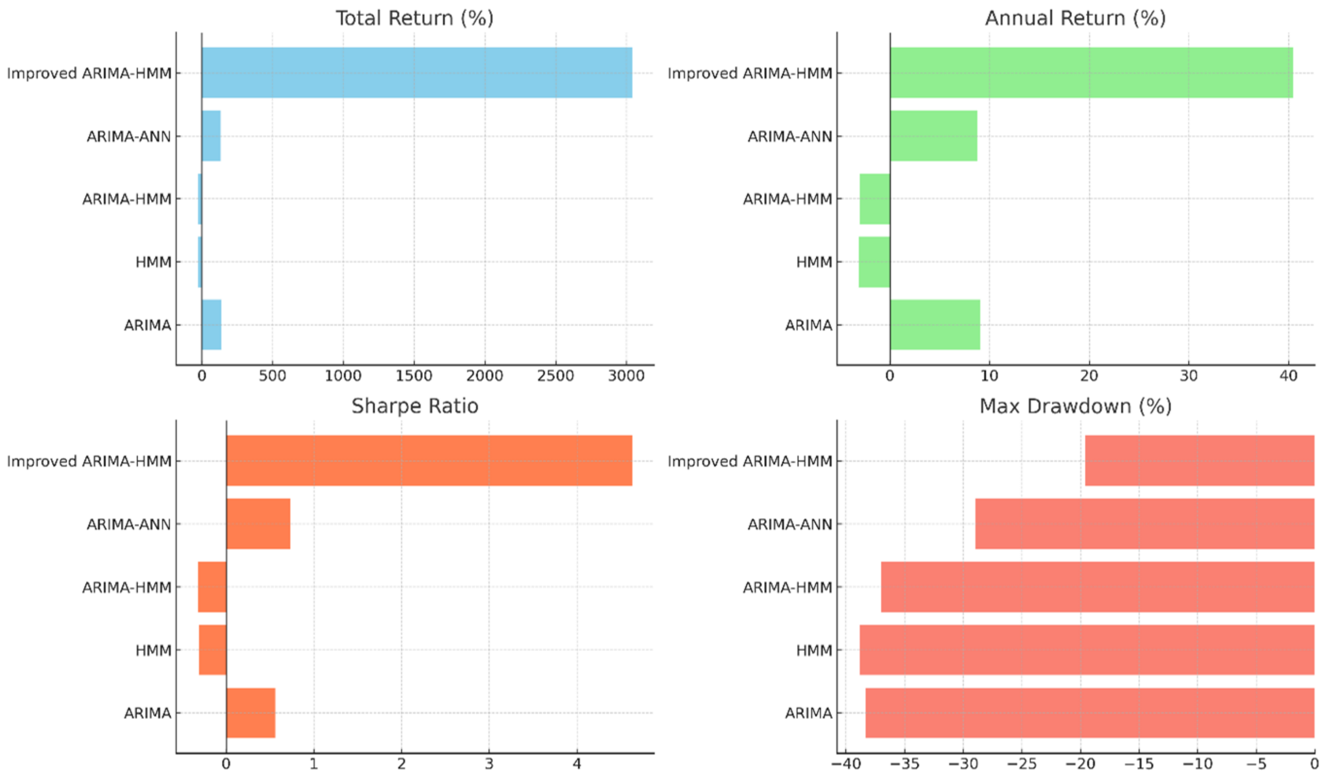

Fig. 6: Performance of Adaptive ARIMA-HMM vs. Baseline Models

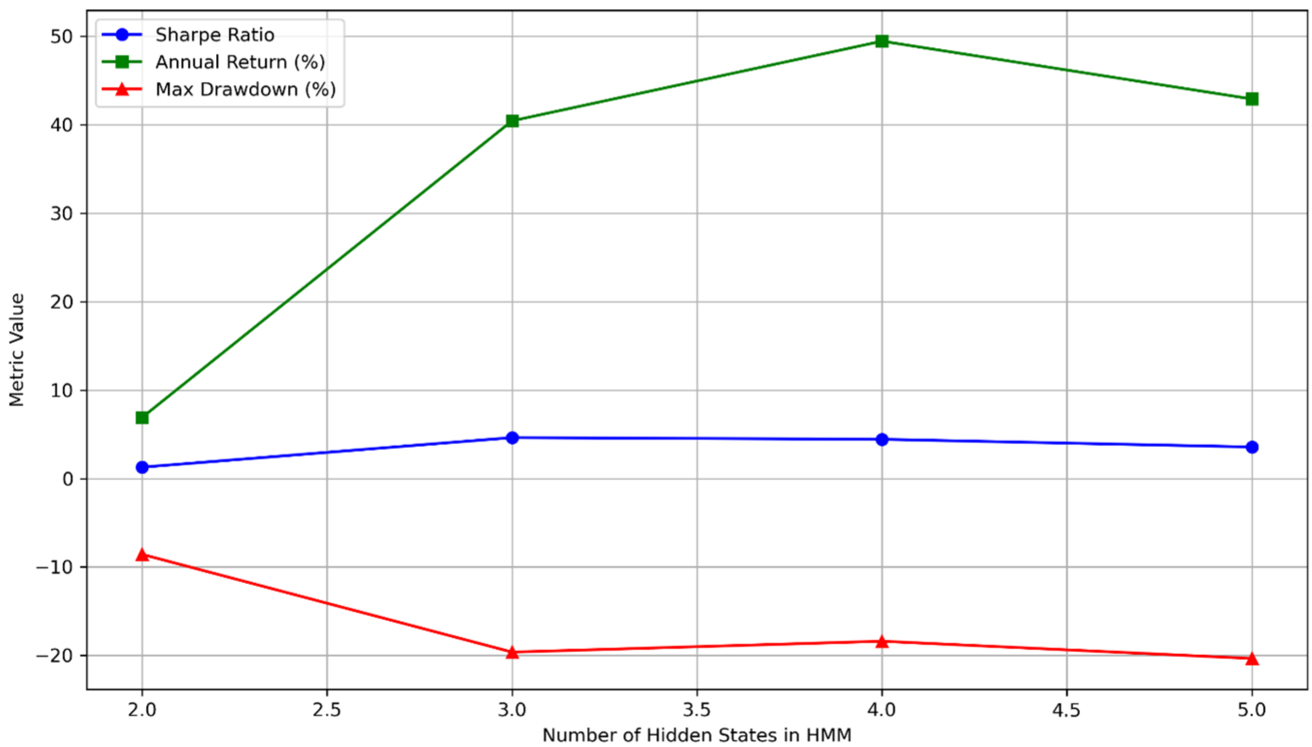

Fig. 7: Sensitivity Analysis of Adaptive ARIMA-HMM Model

this further, elevating returns to an extraordinary 5803.82%, the highest among all configurations. While the Sharpe ratio does dip a bit to 4.44, it is terrific to see that the results are still compelling. Conversely, upon implementing the 5-state model, a decline in performance is observed, characterized by reduced returns, a diminished Sharpe ratio, and the most substantial drawdown of-20.34%, which may indicate potential overfitting. These findings imply that a 3-state Hidden Markov Model (HMM) achieves the optimal equilibrium between profitability and risk. In contrast, a 4-

state model may be an excellent option for those pursuing more aggressive return-maximizing strategies.

Figure 7 shows how performance metrics change alongside hidden states in the Hidden Markov Model (HMM). As we increase the number of states from two to four, the annual return and Sharpe ratio improve significantly, while the maximum drawdown remains manageable. Models incorporating three and four states achieve an optimal equilibrium between performance and risk. Conversely, when the number of states is increased beyond four, a minor decline in both returns and the Sharpe ratio is observed, indicating that introducing additional complexity does not necessarily result in improved outcomes.

VII. Discussion

A. *Comparative Evaluation of Forecasting Models and Investor Implications*

This study explores forecasting models like ARIMA, HMM, ARIMA -ANN, Hybrid ARIMA-HMM, and Adaptive ARIMA-HMM applied to Indian stock market data. We examine their performance in statistical accuracy, market regime detection, and investment performance. As for market characteristics, our initial analysis reveals a gentle upward trend, but we also notice sharp declines that suggest the traditional normality assumptions might need a rethink. Investors require models that adapt to sudden regime shifts and risk escalations. The ARIMA(1, 0, 1) identified minor linear dependencies, achieving 141% returns, but failed to capture non-linear patterns or volatility changes. This model is a fundamental benchmark for passive investors, although its performance deteriorates during volatile periods. The HMM offers a compelling perspective on market behavior by identifying Bull, Bear, and Sideways regimes. Although strategies focusing exclusively on these regimes have not met performance expectations, they highlight the necessity of integrating dynamic allocation strategies to enhance profitability.

The hybrid ARIMA-HMM model enhances our understanding by using HMM techniques to analyze ARIMA residuals, clarifying classification and volatility mapping. However, a complex model without adaptability is insufficient.

B. *Adaptive ARIMA-HMM: A Dynamic and Investor-Centric Forecasting Strategy*

Adaptive ARIMA-HMM approach embraces smoothed regime probabilities, which leads to more dynamic asset allocation and better residual modelling.

This strategy gives investors the flexibility to tailor their equity exposure. They can be fully invested during bullish markets, stay partially invested during sideways markets, and withdraw during bearish phases. This strategy minimizes emotional trading and fosters disciplined investment decisions. With a return of 3040%, a Sharpe ratio 4.63, and a lower drawdown of (-62%), this model surpasses benchmarks and delivers solid risk-adjusted returns, making it an excellent choice for long-term investors looking to grow their capital while reducing downside risks.

C. *Investor Applications:Regime-Based Strategies for Diverse Market Participants*

Both retail and institutional investors can use smoothed regime probabilities for gradual adjustment to their portfolios, thereby improving overall stability. Short-term traders and hedge funds are uniquely positioned to utilize regime probabilities, aiding them in identifying the best entry and exit points in the market. This creates an exciting advantage for strategic planning. By smoothly incorporating regime-based signals across various asset classes, investors can relish the perks of flexible portfolios that effortlessly adapt to changing market conditions, enhancing their opportunities for success.

D. *Insights from Sensitivity Analysis*

Upon diligent refinement of the states within the Hidden Markov Model (HMM), it was determined that integrating three to four regimes yields optimal overall performance. Utilizing merely two states appeared to result in underfitting, whereas implementing five states resulted in overfitting, adversely affecting our metrics. We were gratified to discover that the four-state model attained the highest total return, while the three-state model offered the most favorable risk-return balance.

VIII. Conclusion

This research introduces an Adaptive ARIMA-HMM framework for regime-aware financial forecasting in emerging markets. By applying Hidden Markov Models to ARIMA residuals and incorporating smoothed regime probabilities for dynamic asset allocation, the model captures shifts in market behavior effectively. The three-regime classification—Bull, Bear, and Sideways—guides adaptive exposure rules (100%, 50%, and 0% equity allocation), leading to notable back-tested results: 40.44% annualized returns, a Sharpe ratio of 4.63, and reduced drawdowns to -19.62%. The framework significantly outperforms static hybrids and ARIMA-ANN models.

However, the extremely high cumulative returns (3040.88% and 5803.82% for 3- and 4-regime models) raise concerns about overfitting. The use of smoothed probabilities introduces latency, and the absence of transaction cost modeling may overstate real-world performance. Additionally, misclassification during turbulent periods, such as the 2020 crash, exposes limitations in regime detection.

Despite these caveats, the framework demonstrates the value of combining statistical and probabilistic tools for adaptive forecasting. Future work should integrate real-time macroeconomic triggers, transaction cost modeling, and out-of-sample validation to enhance deployability. The proposed model marks a step forward in interpretable, regime-responsive strategies for financial decision-making in dynamic markets.

REFERENCES

[1] Ahmad W, Bandi K. Identifying regime shifts in Indian stock market: A Markov switching approach. *MPRA Paper No. 37174*, 2012.

[2] Ang A, Timmermann A. Regime changes and financial markets. *Annual Review of Financial Economics*, 4:313–337, 2012.

[3] Badhani KN. Explaining the volatility of aggregate stock returns in India with Markov-Switching-Regime-ARCH model. *Metamorphosis: A Journal of Management Research*, 7:177–201, 2008.

[4] Hamilton JD. A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica*, 57(2):357–384, 1989.

[5] Hu D. Forecast stock market analysis based on Hidden Markov Model and Long Short-Term Memory model—Take the S&P 500 index as an example. *Finance & Economics*, 1, 2024.

[6] Kim CJ, Nelson CR. *State-space models with regime switching: Classical and Gibbs-sampling approaches with applications*. MIT Press, Cambridge, MA, 1999.

[7] Kritzman M, Page S, Turkington D. Regime shifts: Implications for dynamic strategies. *Financial Analysts Journal*, 68(2):22–39, 2012.

[8] Kumar A. A Markov-switching vector error correction model of the Indian stock prices and trading volume. *IGIDR Working Paper*, 2008.

[9] Kumar M, Thenmozhi M. A comparison of different hybrid ARIMA–Neural Network models for stock index return forecasting and trading strategy. *SSRN Paper No. 1009546*, 2007.

[10] Laha AK. Analysis of regime switching behaviour of Indian stock markets. *SCERFA Paper No. 249*, 2006.

[11] McDonald S, Coleman S, McGinnity T, Li Y. A hybrid forecasting approach using ARIMA models and self-organising fuzzy neural networks for capital markets. *Proc. Int. Joint Conf. on Neural Networks (IJCNN)*, pages 1–7, 2013.

[12] Nystrup P, Lindström E, Madsen H, Nielsen SF. Dynamic allocation with hidden Markov models and long/short portfolios. *Quantitative Finance*, 20(4):573–591, 2020.

[13] Palupi I, Wahyudi BA, Putra AP. Implementation of Hidden Markov Model (HMM) to predict financial market regime. *Proc. Int. Conf. on Information and Communication Technology (ICOICT)*, 2021.

[14] Rabiner LR. A tutorial on Hidden Markov Models and selected applications in speech recognition. *Proc. IEEE*, 77(2):257–286, 1989.

[15] Ratnayaka RMKT, Seneviratne DMKN, Jianguo W, Arumawadu HI. A hybrid statistical approach for stock market forecasting based on Artificial Neural Network and ARIMA time series models. *Proc. Int. Conf. on Behavioral, Economic, and Socio-Cultural Computing (BESC)*, pages 54–60, 2015.

[16] Sharpe WF. The Sharpe ratio. *Journal of Portfolio Management*, 21(1):49–58, 1994.

[17] Srivastava S. Predicting regimes in the Indian market with macroeconomic data and machine learning. *SSRN Paper No. 4649699*, 2023.

Dr. Jyoti Badge was born in 1979 in Bhopal, Madhya Pradesh. She completed her graduation in Mathematics from Govt. M.L.B. Girls P.G. College, Bhopal, in 2000, followed by a master's degree in Statistics from Govt. Motilal Vigyan Mahavidyalaya, Bhopal, in 2003. She earned her Ph.D. in Applied Mathematics from Maulana Azad National Institute of Technology (MANIT), Bhopal, in 2012. Currently, she serves as an Assistant Professor at VIT University, Bhopal, with over 15 years of teaching experience in Statistics. Her research and teaching interests include Business Mathematics, Business Statistics, Quantitative Techniques, and Econometrics for Finance.

Mr. Badrikanath Praharaj is a final-year Electronics and Communication Engineering student at VIT Bhopal, specializing in intelligent systems development. As a Research Intern at IISc Bangalore's RBCCPS laboratory, he has contributed to 10+ scholarly publications in artificial intelligence, computer vision, and autonomous robotics. His work in these domains was recognized with a 3rd place award in a national research competition. While primarily focused on neural network optimization and robotic agent training, he maintains active academic discourse on emerging machine learning paradigms. He seeks to advance innovation at the intersection of hardware engineering and intelligent systems through collaborative research initiatives.

Mr. Dnyanesh Kavate is a final-year Computer Science student at VIT Bhopal, specializing in secure machine learning systems. With an internship on Cyversecurity, he developed defenses against adversarial attacks and contributed to 3 research papers on LLM security and optimization. His technical work includes building production-grade large language models and implementing low-latency inference engines in Python, C, and C++. Proficient across the ML stack—from neural architecture design to model hardening—he has engineered systems . Mr. Kavate's current research focuses on efficient fine-tuning for edge devices, aiming to bridge security gaps in real-world AI deployments.