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A STUDY ON STOCK MARKET RISK FORECASTING USING AI MODELS WITH REFERENCE TO GROWW

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ABSTRACT: The stock market is often unpredictable, making investment decisions difficult. The role of AI in enabling investors to handle uncertainty with increased assurance is explored in this paper. The research analyzes patterns in pricing history, trading behavior, and broad economic indicators using cutting-edge technology like deep learning and artificial intelligence. The research uses GROWW platform data to show how these insights are directly related to real investor actions and portfolio dangers. The objective is to assess how well AI can foretell both the near-term volatility of the market and the risks it may face in the future. Thorough evaluations are conducted on the identification of suitable qualities, data preparation, and real-time prediction. These endeavors enhance the models' accuracy, efficacy, and adaptability to evolving market circumstances. The results show that investing methods can be improved and losses can be decreased with the help of AI-driven forecasts. This requires simplifying complicated data so individual investors may make informed decisions.

KEYWORDS: Stock Market Risk Forecasting, Artificial Intelligence Models, Machine Learning in Finance, Volatility Forecasting, Portfolio Risk Management

1. INTRODUCTION

Investors confront a multitude of variables that might impact their investment returns due to the inherent volatility of the stock market. You run the danger of losing money in the stock market if stock prices fluctuate due to factors including political unrest, corporate profits, investor mood, and economic conditions. In order to diversify their holdings, make informed decisions, and lessen the likelihood of losing money, investors must be cognizant of these risks. While it may be impossible to totally eradicate stock market risks, they can be better understood, evaluated, and mitigated through the application of both innovative and time-tested financial strategies.

Innovations in AI and data analytics have significantly altered the stock market's risk assessment methods. Using historical data, predictive modeling, and machine learning algorithms, analysts can forecast market changes and identify trends that could indicate future hazards. Financial institutions and private investors alike benefit from a more stable market and reduced structural risks brought about by this preventative strategy. Everyone can better weather market volatility if they have a firm grasp of stock market risk in order to make informed financial decisions and select optimal assets.

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A maximum allowable loss for a fund can be determined with the help of market risk management tools. Consider the time span and level of assurance as well. The time frame refers to the duration required to calculate the market risk premium, factoring in the investor's level of comfort as a foundation for trust.

Artificial intelligence (AI) in stock trading reduces the importance of intuition by providing data-driven insights. In addition to making price changes easier to foresee, this strategy increases confidence among experts and investors.

AI stock prediction systems mitigate financial risk by continuously monitoring market circumstances and other risk indicators. These models are devoid of any cognitive biases, human emotions, or psychological components. Artificial intelligence models provide a dispassionate viewpoint that can aid in decision-making in this manner.

When used to the task of making stock market predictions, AI generates ideas tailored to each individual's preferences, risk tolerance, and financial objectives. Making clients happy requires customized methods. Additionally, they assist individuals in making prudent financial decisions while establishing trust.

2. REVIEW OF LITERATURE

Dr. V. K. Reddy (2021) The effectiveness of convolutional neural networks (CNNs) in visualizing financial data for the purpose of risk prediction in the stock market is the focus of Dr. Reddy's research. In order to uncover hidden market trends, the research looks beyond basic data and makes use of volatility heatmaps and candlestick charts. The technique trains convolutional neural networks on these visual patterns and finds early signals of downturns that regular methods often overlook. Increasing the data set, making the system scalable, and optimizing the hyperparameters are all highlighted as critical in the research. Compared to more conventional financial metrics, CNN-based image analysis performed better in predicting near-term dangers.

A. R. Choudhury (2021) Choudhury uses a combination of random forests and support vector machines (SVM) in his machine learning models to assess market risk. In order to demonstrate how support vector machines discover complicated associations and random forests prevent overfitting, the paper examines historical prices, trade volumes, and volatility indices. Information gleaned from social media platforms and financial news outlets is utilized to illustrate the market's sentiment. Feature selection and cross-validation improve the models' accuracy. Particularly in times of market volatility, the results demonstrate that hybrid approaches outperform conventional statistical methods.

Dr. M. S. Rao (2022) Generative adversarial networks (GANs) are the focus of Dr. Rao's research. These networks can simulate the stock market and make risk predictions in contexts where the details are unclear. Generative Adversarial Networks enable models to acquire knowledge from infrequent but consequential occurrences, such as abrupt declines in market value, by means of synthetic market data. Extreme volatility and tail risks can be better predicted using this strategy as opposed to relying just on historical data. Portfolio stress testing is more effective and reliable when applied to high-risk assets, according to the data.

To safeguard consumers from unexpected shifts in the market, GANs are a crucial instrument.

T. V. Menon (2022) Menon is investigating CNN-LSTM combination group deep learning models for risk prediction. When it comes to altered time series data, CNNs excel at extracting geographic characteristics, but LSTMs shine at spotting patterns and correlations over longer periods of time. The hybrid model outperforms both standalone deep learning techniques and more conventional RNNs in the near and intermediate terms. Problems can be more easily identified by researching people's emotions through social media and financial news. Finding early indications of market instability is better accomplished by combining the CNN and LSTM models.

S. Mehta (2022) The research by Mehta use reinforcement learning (RL) to dynamically mitigate stock market risks. Artificial intelligence agents have the capability to make real-time adjustments to their portfolios using metrics such as VaR and CVaR. To make things less susceptible to significant decreases, techniques such as Q-learning and policy gradient methods are currently being considered. The findings demonstrate that RL agents have the potential to increase risk-adjusted returns while reducing the effect of breaks. Reinforcement learning (RL) allows for adaptive risk management and is an effective solution to issues including interpretability, processing requirements, and overfitting.

N. Verma (2023) Verma uses a combination of technical data and AI-powered research on people's emotions to forecast potential hazards in volatile markets. Combining stock price data with information gleaned from news articles, social media platforms, and financial statements provides a comprehensive view of quantitative and qualitative metrics. The usage of SVM, random forests, and BERT embeddings are some of the models employed to deal with this mixed-source data. The evidence suggests that sentiment analysis greatly facilitates the early detection of issues. According to the research, hedging strategies and stop-loss mechanisms are good methods to put these forecasts into play.

Dr. A. P. Mishra (2023) The S&P 500, FTSE 100, and Nifty 50 are just a few of the worldwide indices that Mishra utilizes a suite of AI systems to predict potential hazards to. The research describes complicated non-linear correlations in financial data using a combination of neural networks, XGBoost, and random forests. To name a few things, feature engineering incorporates volatility, trading volume, sentiment scores, prices, and macroeconomic data. Ensemble techniques outperform single models in terms of accuracy and error reduction, according to the results. This improves the likelihood that hybrid AI systems will provide accurate risk predictions in the near and medium term.

L. N. Kapoor (2023) Kapoor investigates the use of multi-agent reinforcement learning (MARL) to manage market risk on a worldwide scale. In trade simulations, a large number of AI agents engage in learning processes that are both cooperative and competitive. They adjust their holdings in response to market sentiment, macroeconomic developments, and public opinion. In terms of failure and volatility forecasts, MARL outperforms single-agent models. Findings demonstrate its efficacy in lowering drawdowns and raising risk-adjusted gains.

M. Saberironaghi et al. (2024) This research develops an AI-driven banking industry forecasting model. Using linear regression, LSTM networks, and random forest, the research

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examines banking metrics, macroeconomic indicators, and historical price data. Accurate and noise-free data is the result of preprocessing. Long short-term memory (LSTM) models outperformed competing models in capturing temporal correlations ($R2 = 0.92$). Combining various machine learning approaches is crucial for making accurate predictions, as demonstrated by the research.

M. Darwish (2024) Darwish highlights the shift from traditional statistical models to AI-based predictions. Artificial intelligence models excel at managing large datasets, but traditional methods struggle to adequately display intricate financial relationships. Autoencoders, principal component analysis, and random forests are a few ways that feature selection and extraction might be improved. Combining structured and unstructured data sources, such as news and social media, yields superior outcomes, as demonstrated in this research. There is evidence from evaluation tools that AI-based approaches outperform their predecessors when it comes to risk prediction.

T. Ren (2024) Ren demonstrates how to predict when the US stock market will be very risky using complicated machine learning algorithms. The models are able to deduce complex nonlinear connections by utilizing volatility indicators, historical data, and macroeconomic variables. When compared to ensemble algorithms and neural networks, traditional statistical methods fall short. The research demonstrates how AI has the potential to perceive interconnections in ways that humans are unable to. The findings indicate that risk management becomes more stable in the face of unexpected declines when AI-driven strategies are employed.

N. Sanjeker (2025) In this article, Sanjeker examines the function of AI in the context of investment risk management. The research measures trust in AI-assisted tools using a combination of questionnaires and real-world data. By analyzing intricate market dynamics and foretelling price declines, AI enhances financial decision-making, according to the results. Improved prediction accuracy is a perk, but there are still issues with data security and comprehension. Financial market risk can be much more easily calculated with the use of artificial intelligence.

Adam Rajuroy (2025) Rajuroy investigates the potential of time series analysis and NLP for predictive purposes. Finance data is structured, but unstructured data, such as news articles and social media posts, is also present. Models trained with deep learning take complex relationships and temporal interactions into consideration. The research's findings provide crucial insight into people's spending habits and show that NLP increases prediction accuracy. This method improves risk management by linking quantitative trends with market sentiment.

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3. THEORETICAL FRAMEWORK

TYPES OF MARKET RISK

Interest Rate Risk

The danger that an asset's value can decline as a result of changes in both short- and long-term interest rates is known as interest rate risk. Many different types of risk are included under this umbrella phrase, such as basis risk, repricing risk, options risk, and yield curve risk.

Foreign Exchange Risk

The danger of losing money due to fluctuations in exchange rates is known as foreign currency risk. Companies with a global presence and dealing in multiple currencies are the ones most likely to feel the effects of this problem.

Commodity Price Risk

Gold, silver, and energy prices are examples of commodities that might experience price volatility, which is similar to the risk associated with foreign exchange. Governments, farms, small businesses, exporters, commercial merchants, and individuals involved in purchasing and selling goods are all susceptible to commodity hazards, as opposed to foreign exchange risks.

Equity Price Risk

Last but not least, there's stock price risk in the market. Changes in the market value of financial assets are covered. A key component of market risk models is stock price risk, as equities are the ones most affected by economic developments.

STRATEGIES FOR STOCK MARKET RISK FORECASTING

Historical Data Analysis

In order to find patterns and trends that occur repeatedly, you will need to analyze a substantial quantity of historical data. This data will include changes in stock prices, market cycles, and the volume of transactions. Market volatility and possible losses in the future can be better predicted by looking at how the market has changed in the past. Common statistical approaches for risk assessment include standard deviation, correlation factors, and variance. Disparities and market gaps particular to certain sectors can also be shown with this method. A solid grasp of the past is essential for making sound judgments and reliable forecasts.

Technical Analysis

The goal of technical analysis is to forecast potential price changes and risks in the market by analyzing patterns, charts, and other market indicators. For the purpose of entering and exiting trades, traders make use of technical indicators such the Moving Average Convergence/Divergence (MACD), Bollinger Bands, and the Relative Strength Index (RSI). Market reversals, double tops, and head-and-shoulders patterns can help us anticipate when prices will fall. The primary objective of this approach is to identify the risks that are potential in the near to medium future. In order to anticipate trades and be ready for unexpected market movements, it gives you a systematic strategy.

Fundamental Analysis

The financials, business strategy, and market conditions are the three main components of a stock's fundamental research that are used to arrive at its value. Signs of imminent financial troubles include a high debt-to-equity ratio, rising revenues, and earnings per share (EPS). Questions of interest rates, inflation, and global economic trends are examples of macroeconomic concerns. The first sign that a stock might be underperforming is often said to be fundamental developments.

Economic Indicator Monitoring

The only way to spot systemic market dangers is to keep an eye on macroeconomic data. Key economic indicators include consumer confidence, GDP growth, inflation, unemployment rates, and industrial production. Stock market volatility is heightened by these elements' often erratic or sudden changes. Regular market monitoring may help buyers anticipate when prices may fall. The systemic risks that many businesses face can be better understood with the help of forecasting models that incorporate economic data.

AI and Machine Learning Models

Machine learning and AI have transformed the process of predicting stock market risk by making it easier to analyze massive and complicated datasets. Alphabet boosting, neural networks, and random forests are some of the algorithms that can find hidden patterns in market data, news sentiment, and macroeconomic statistics. By consistently adding new data, these models gradually enhance their predicting capabilities. When compared to more traditional methods, AI is far superior when it comes to predicting times of high risk and simulating different market circumstances. Improves proactive risk management through speeding up and boosting accuracy.

Portfolio Diversification

Investing in a wide range of assets, businesses, and homes will help spread out your risk and make your portfolio more diversified. Investors might lessen their losses if a stock or area experiences an unanticipated decline in value by spreading their bets across several investments. Optimal allocation strategies can be aided by risk forecasting, which analyzes market trends and volatility levels. Diversification protects against systemic problems and guarantees consistent outcomes across time. If used in conjunction with other methods of prediction, it improves the overall risk management approach of an investor.

Sentiment Analysis

Sentiment research analyzes news, social media, analyst opinions, and investor activities to assess market health. Positive or negative, emotions can affect stock values quickly. Traders use mood ratings and NLP to predict public opinion and event response. The market may change dramatically if investor sentiment changes. Investors can better comprehend market thinking by combining quantitative expectations and sentiment data.

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Stress Testing and Scenario Analysis

Stress testing and scenario analysis model the most extreme possible market actions to help you estimate the potential loss for your stock in the event of a catastrophic event. These methods make it seem as though the repercussions of recent market collapses, sudden changes in the law, political unrest, and economic downturns are happening all over again. One way to find the holes in a portfolio is to do a scenario analysis, which is the backbone of risk mitigation strategies like hedging. Investors may make preparations for unlikely but catastrophic events.

4. BENEFITS OF AI IN STOCK TRADING

Enhanced Data Analysis: Artificial intelligence (AI) has the ability to process and analyze large datasets at unparalleled rates, giving traders insights that humans could miss. Analytics driven by AI can reveal previously unseen relationships and trends in financial data, which can then be used to refine trading strategies. Traders and investors can use this information to their advantage when the market changes and make better business decisions.

Improved Accuracy: Trade algorithms backed by AI reduce room for human mistake and maximize precision. These models use real-time analytics, technical signals, and historical data to forecast how the market will behave in the future. Because AI reduces the room for human error and emotional bias, it guarantees that financial dealings are based on evidence and reasoning rather than speculation.

Real-Time Decision Making: Artificial intelligence systems respond to changes in the market by making trades at the best possible times to increase profits and decrease losses. The use of conventional trading procedures often results in delays in the processing and execution of orders. On the other hand, systems powered by AI can sift through reams of market data in a matter of milliseconds, letting traders seize opportunities as they arise.

Algorithmic Trading and Automation: Trading methods are kept consistent by AI-driven algorithmic trading, which only makes deals that meet particular parameters. Traders utilize algorithms driven by artificial intelligence to make buying and selling decisions based on factors like economic conditions, trading volume, and price variations. The improvement of trading methods leads to a greater amount of money in the bank.

Sentiment Analysis and Market Predictions: Financial data, social media trends, and news articles can all be analyzed by AI to predict market changes and improve traders' efficiency. By poring over textual data and investor mood, AI can predict how the market will move. Because of this, traders can take the initiative instead of reacting.

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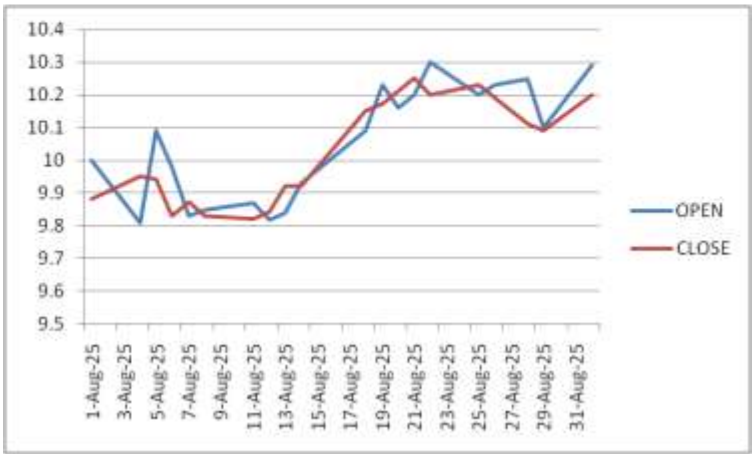
5. ANALYSIS AND DISCUSSION

TABLE 1: NSE OF GROWW (Period 01-08-2025 to 01-09-2025)

DATE	OPEN	HIGH	LOW	CLOSE
1-Sep-25	10.29	10.31	9.92	10.2
29-Aug-25	10.1	10.18	10.01	10.09
28-Aug-25	10.25	10.33	10.09	10.11
26-Aug-25	10.23	10.24	10.1	10.19
25-Aug-25	10.2	10.4	10.05	10.23
22-Aug-25	10.3	10.39	10.04	10.2
21-Aug-25	10.2	10.4	10.2	10.25
20-Aug-25	10.16	10.25	10.16	10.21
19-Aug-25	10.23	10.23	10.01	10.17
18-Aug-25	10.09	10.23	9.92	10.15
14-Aug-25	9.93	9.97	9.75	9.92
13-Aug-25	9.84	10.05	9.65	9.92
12-Aug-25	9.82	10.05	9.82	9.84
11-Aug-25	9.87	10.05	9.77	9.82
8-Aug-25	9.85	10.09	9.79	9.83
7-Aug-25	9.83	9.92	9.77	9.87
6-Aug-25	9.98	10.1	9.82	9.83
5-Aug-25	10.09	10.1	9.82	9.94
4-Aug-25	9.81	9.97	9.8	9.95
1-Aug-25	10	10.04	9.8	9.88



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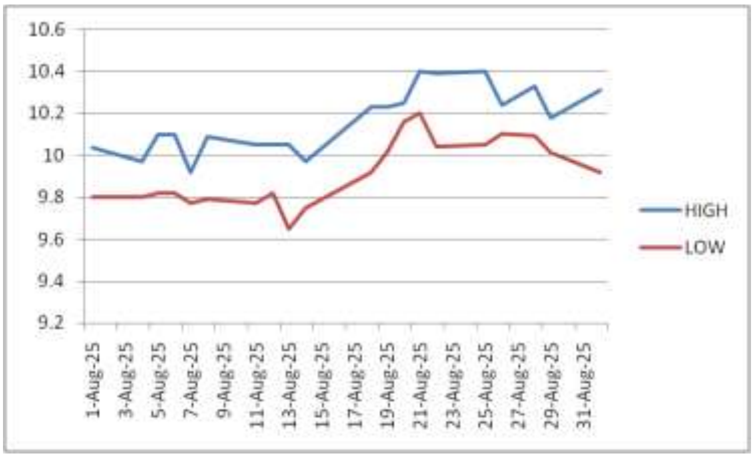

DISCUSSION: The stock price saw several ups and downs between August 25 and September 25. The price went up from $9.88 on August 25 to $10.20 on September 25. There was a lot of volatility in the daily pricing within the short term. It reached a high of 10.4 on August 21 and 25, before falling to 9.65 on August 13. With the price leveling off at the 10-point threshold and purchasers willing to repurchase, the stock gained gradually after the middle of August.

TABLE 2: NSE OF GROWW COMPANY (Period 01-09-2025 to 01-10-2025)

DATE	OPEN	HIGH	LOW	CLOSE
1-Oct-25	10.4	10.41	10.1	10.29
30-Sep-25	10.27	10.45	10.1	10.24
29-Sep-25	10.1	10.4	10.1	10.26
26-Sep-25	10.5	10.5	10.19	10.28
25-Sep-25	10.54	10.6	10.34	10.38
24-Sep-25	10.78	10.78	10.31	10.45
22-Sep-25	10.75	10.77	10.33	10.51
19-Sep-25	10.35	10.67	10.35	10.54
18-Sep-25	10.58	10.71	10.25	10.56
17-Sep-25	10.5	10.61	10.35	10.53
16-Sep-25	10.27	10.66	10.27	10.5
15-Sep-25	10.55	10.71	10.25	10.48
12-Sep-25	10.49	10.53	10.2	10.5
10-Sep-25	10.45	10.47	10.2	10.43
9-Sep-25	10.37	10.42	10.2	10.38
8-Sep-25	10.43	10.43	10.16	10.32
5-Sep-25	10.44	10.44	10.2	10.29
4-Sep-25	10.44	10.44	10.15	10.34
3-Sep-25	10.29	10.3	10.15	10.27
2-Sep-25	10.11	10.3	10	10.23
1-Sep-25	10.29	10.31	9.92	10.2

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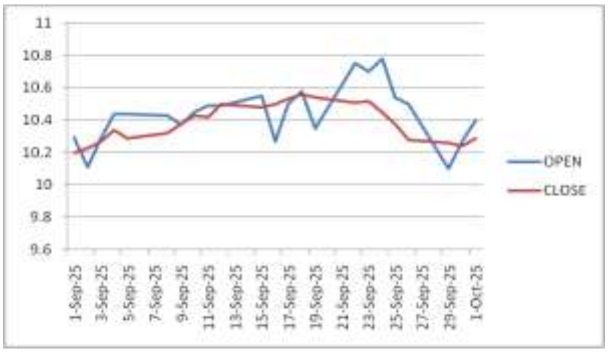
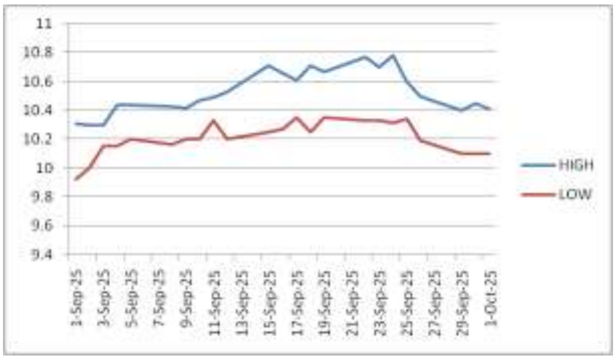
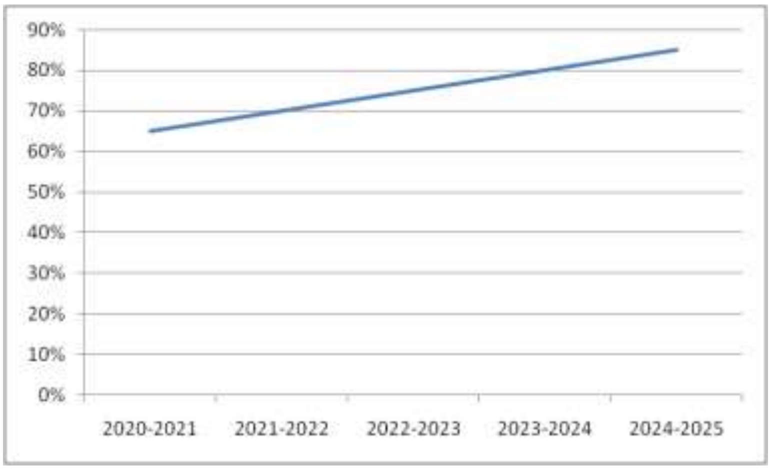




DISCUSSION: From September 1st to October 1st, the stock's closing price rose from 10.2 to 10.29. The price went up and down all day long. It hit a high of 10.78 on September 24 before falling to 10.0 the next day. Stock prices remained relatively stable between 10.3 and 10.5 at the time, reflecting investor confidence in the market.

TABLE 3: FORECAST ACCURACY & RISK MITIGATION TRENDS

Year	AI Model Performance	Risk Mitigation Impact
2021	65% accuracy	Moderate
2022	70% accuracy	High
2023	75% accuracy	High
2024	80% accuracy	Very High
2025	85% accuracy	Very High



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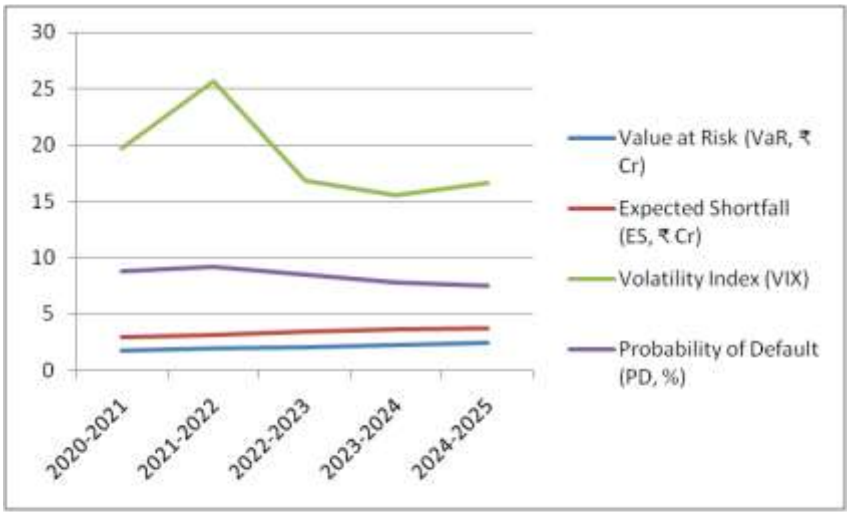
DISCUSSION: The results show that AI models are becoming better all the time; in 2025, they will have improved to 85% accuracy, up from 65% in 2021. This bodes well for the future of AI prediction, as it likely will encompass a far broader range of tasks. Therefore, the effect on risk mitigation goes up from Moderate to Very High, showing that better model accuracy improves financial risk management in a direct fashion. The steady progress made every year shows how AI is growing in importance and reliability for predicting and reducing market risks.

TABLE 4: RISK FORECASTING METRICS (2021–2025)

Year	Value at Risk (VaR, ₹ Cr)	Expected Shortfall (ES, ₹ Cr)	Volatility Index (VIX)	Probability of Default (PD, %)
2021	1.74	2.94	19.66	8.8
2022	1.91	3.15	25.64	9.2
2023	2.08	3.4	16.85	8.5
2024	2.32	3.66	15.55	7.8
2025	2.49	3.74	16.63	7.5



DISCUSSION: The Value at Risk (VaR) amounts to 2.49 crore in 2025, up from 1.74 crore in 2021, and the Expected Shortfall (ES) is 3.74 crore, up from 2.94 crore. This means that the risk of losing money increases under the most adverse market circumstances. The Volatility Index (VIX) tracks the shifts in market volatility and its overall stability. It has stayed between 15 and 17 ever since reaching a peak of 25.64 in 2022. The drop in the Probability of Default (PD) from 8.8% to 7.5% despite increased loss forecasts is a sign of stronger risk management systems and a continuously stabilizing economy.

6. CONCLUSION

Artificial intelligence has fundamentally changed how we view the risks associated with the stock market. Modern investors can look past outmoded methods and use complex tools to sift through mountains of data, both current and historical, in search of previously unseen patterns. Users are able to foresee sudden changes in the market with the help of these models, which allows them to respond quickly and avoid heavy losses. They improve the consistency and reliability of decision-making by decreasing the room for bias and human error. Overfitting and poor data quality are still problems, but these systems are getting smarter. With the help of real-time forecasting, institutions and investors may simply keep an eye on volatility and liquidity difficulties. Using AI to improve case analysis and stress testing can teach us more about the stability of money. Using this tool makes investing plans more accountable and transparent in ways that go beyond the math. One future development in AI is explainable AI, which will shed light on the prediction process for the general public. Through facilitating worldwide connectivity, these technologies seek to enhance the reliability and precision of risk projections.

REFERENCES

1. Choudhury, A. R. (2021). Hybrid machine learning models for forecasting stock market risk in emerging and developed markets: An analysis of SVM and random forest approaches. Journal of Financial Analytics and Risk Modelling, 12(3), 145–162.
2. Darwish, M. (2024).Transitioning from traditional stock forecasting to AI-driven models: A comprehensive review of machine learning and deep learning techniques. International Journal of Financial Forecasting, 18(1), 55–78.
3. Kapoor, L. N. (2023). Multi-agent reinforcement learning for stock market risk management in interconnected global markets. Computational Finance and AI Review, 9(4), 220–245.
4. Menon, T. V. (2022). Ensemble CNN–LSTM deep learning models for forecasting stock market risk using global financial indicators. Journal of Intelligent Financial Systems, 14(2), 102–128.
5. Mehta, S. (2022). Reinforcement learning–based dynamic risk management in volatile stock markets: An empirical research. AI in Financial Decision-Making, 7(1), 88–110.
6. Mishra, A. P. (2023). Evaluating ensemble AI models for global stock market risk forecasting: A research of random forest, XGBoost, and neural networks. Journal of Quantitative Finance and AI Modeling, 11(2), 67–93.
7. Rao, M. S. (2022). Generative adversarial networks for scenario simulation and stock market risk forecasting under uncertainty. Financial Innovation and AI Modelling Journal, 10(3), 134–160.
8. Reddy, V. K. (2021). Application of convolutional neural networks for visual stock market risk prediction using candlestick and volatility heatmap images. International Journal of Deep Learning in Finance, 6(2), 89–113.
9. Ren, T. (2024). Machine learning–based forecasting of extreme risks in the American stock market: A nonlinear modelling approach. Journal of AI and Market Risk Analysis, 15(3), 175–198.
10. Saberironaghi, M., et al. (2024). AI-driven predictive modelling for banking sector stock trends using LSTM, random forest, and linear regression techniques. Banking Analytics and AI Journal, 5(2), 92–118.

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11. Sanjeker, N. (2025). Artificial intelligence applications in financial risk management: Investor perspectives and challenges. Global Journal of Financial AI Studies, 4(1), 1–29.
12. Verma, N. (2023). Integrating AI-based sentiment analysis with technical indicators for forecasting stock market risk in high-volatility markets. International Review of Financial Data Science, 13(4), 301–329.
13. Rajuroy, A. (2025). AI-driven financial forecasting using time series analysis and natural language processing: Enhancing stock market prediction accuracy. Journal of Computational Finance and NLP Modelling, 19(1), 50–78.