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AI in Derivatives Market in India

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Abstract

This paper investigates the application of Artificial Intelligence (AI) in pricing and valuing derivatives in India's financial markets. While AI is being widely used in global markets for various purposes, very few research papers focus specifically on its application in India's derivatives segment, creating a significant research gap. This paper discusses in detail how AI can be integrated into different pricing and valuation models such as the Black-Scholes model, Monte Carlo simulation, sentiment analysis, and machine learning methods, as well as in risk management, to enhance both accuracy and speed.

Traditional models like Black-Scholes, though well-established, face certain limitations in practical scenarios, especially under volatile market conditions. AI has the ability to overcome these constraints by providing faster, more adaptive, and more precise results, based on real-time data processing and advanced pattern recognition. Monte Carlo simulation, when enhanced with AI algorithms, can handle complex datasets more efficiently, while sentiment analysis powered by AI can assess market mood and its impact on pricing.

The study also highlights that derivatives trading in India has seen significant growth after the COVID-19 pandemic, with more retail investors entering the market and a notable rise in algorithm-based trading practices. Despite these developments, India is still in the process of building a strong AI infrastructure compared to countries in the Western world, where AI integration is more advanced and widespread. However, India is steadily moving towards a more automated and technology-driven derivatives market. This research is relevant for investors, traders, and institutions seeking better decision-making through the adoption of modern.

KEYWORDS – Derivatives, Artificial Intelligence, Neural Networks, Machine Learning

JEL Classification- D83, G13 and C45

1. Derivatives Market in India

The derivatives market in India, which began in the early 2000s, is considered a highly risky form of investment. According to the Securities and Exchange Board of India (SEBI), a derivative is a financial contract whose value is based on an underlying asset. These underlying assets may include commodities such as grains, coffee, and orange juice; precious metals like gold and silver; foreign currencies and exchange rates; bonds issued by governments or companies; shares, share warrants, and stock indices; short-term securities such as Treasury bills; and over-the-counter (OTC) money market instruments, including loans and deposits (Vashishtha and Kumar, 2010). The derivatives market comprises three key categories of participants: hedgers, speculators, and arbitrageurs. Hedgers aim to manage risk by fixing prices to protect themselves from unfavorable market movements, speculators deliberately assume risk in the expectation of profiting from market volatility, and arbitrageurs exploit price inefficiencies across different markets to generate risk-free returns. Together, these participants contribute to the efficiency, liquidity, and stability of the market.

From a structural perspective, the derivatives market can be broadly classified into forward commitments and contingent claims. Forward commitments impose a legal obligation on both parties to execute the contract under predetermined terms at a specified future date, regardless of changes in market conditions. This category includes three main types of instruments: forwards, futures, and swaps. A forward contract is a customized agreement between two parties in which the buyer commits to purchasing an underlying asset from the seller at a predetermined price on a specified future date, with settlement taking place either through physical delivery or cash settlement. Futures contracts are similar in nature but are standardized agreements traded on organized exchanges, which offer greater liquidity, transparency, and safeguards against counterparty default compared to forwards. Swaps are contractual arrangements in which two parties agree to exchange streams of cash flows or other financial instruments, most commonly involving interest payments where one party pays a fixed rate and the other a floating rate.

In contrast, contingent claims grant the right, but not the obligation, to fulfill the terms of the contract, with the most prominent example being options. An option is a financial instrument that gives its holder the right, but not the obligation, to buy or sell an underlying asset at a specified strike or exercise price within a certain period. A call option provides the right to purchase the asset, while a put option grants the right to sell it, with the seller of the option being obligated to fulfill the transaction if the buyer chooses to exercise the right. This flexibility distinguishes options from forward commitments, as the payoff is contingent upon the decision of the holder and market movements.

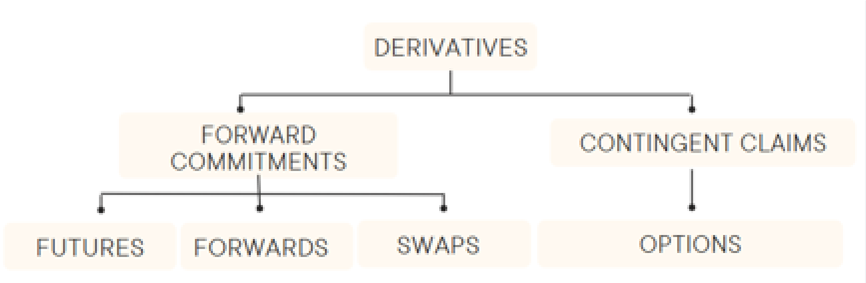

Figure 1- Derivatives in India

Source: Authors self-generated

The regulatory framework for commodity derivatives in India dates back to the establishment of the Forward Markets Commission (FMC) in 1953 under the Forward Contracts (Regulation) Act, 1952. Operating under the Ministry of Finance, the FMC was entrusted with overseeing the commodity derivatives market and regulating 22 commodity exchanges across the country, ensuring that trading practices remained transparent, efficient, and compliant with statutory provisions. The regulatory system comprises the Government of India, the FMC, and the commodity exchanges (Bhagwat and Maravi, 2016)), working collectively to maintain the integrity and stability of the market. Over the years, this framework has played an important role in shaping the evolution of the derivatives market by providing oversight, reducing systemic risk, and fostering investor confidence.

A study by Srikumar, Tattikota, and Kappagantula (2022) provides valuable demographic insights into the Indian derivatives market. The findings reveal that male investors dominate participation, with the majority belonging to the 20–40 age group, a trend reflecting the high-risk nature of derivatives and the appeal they hold for relatively younger investors willing to assume significant market risk. Educationally, 60% of participants hold professional qualifications, while the remaining 40% possess basic degrees, suggesting that higher education and technical knowledge may influence participation. In terms of income distribution, high-earning individuals represent the largest share of derivative investors, indicating that substantial disposable income may be an important factor in engaging with high-risk financial instrument.

1.1 Post-COVID Shifts

The COVID-19 pandemic was an unprecedented and rare event that exerted a profound and far-reaching impact on global financial markets, with the Indian derivatives market experiencing particularly notable disruptions. Investor fear escalated sharply in the aftermath of the World Health Organization's declaration of COVID-19 as a global pandemic, an atmosphere of uncertainty that was further compounded by India's nationwide lockdown and the emergency policy interventions announced by the Reserve Bank of India. During this turbulent period, the India VIX—commonly referred to as the "fear index"—witnessed a rapid and sustained spike, serving as a clear indicator of heightened anxiety and stress among investors. In the derivatives segment, futures prices experienced a steep and abrupt decline, in some instances even trading below the corresponding spot prices. Such pricing anomalies not only reflected severe market dislocation but also contributed to widespread panic among market participants. This chain reaction of uncertainty led to accelerated sell-offs, which in turn amplified panic selling, created margin pressures, and introduced significant inefficiencies in the overall pricing mechanism.

By approximately June 2020, early signs of market normalization began to emerge, as the India VIX gradually started to decline—though it continued to remain elevated compared to its pre-pandemic levels. Over the subsequent months, market conditions steadily improved, paving the way for a sharp resurgence in derivatives trading volumes. This revival of activity firmly positioned India among the largest derivatives markets in the world in terms of volume traded. One of the most remarkable outcomes of this post-pandemic recovery phase was the substantial surge in retail investor participation. As of April 2024, India had approximately 154 million trading accounts, marking an extraordinary increase of more than four times from the 36 million accounts recorded in April 2019. Similarly, the number of active derivatives traders witnessed significant expansion, rising from 0.8 million in 2019 to 4 million by 2023. This substantial growth in both account openings and active participation underscored a fundamental transformation in India's derivatives market, illustrating how the post-pandemic era not only restored but greatly enhanced market engagement and activity levels.

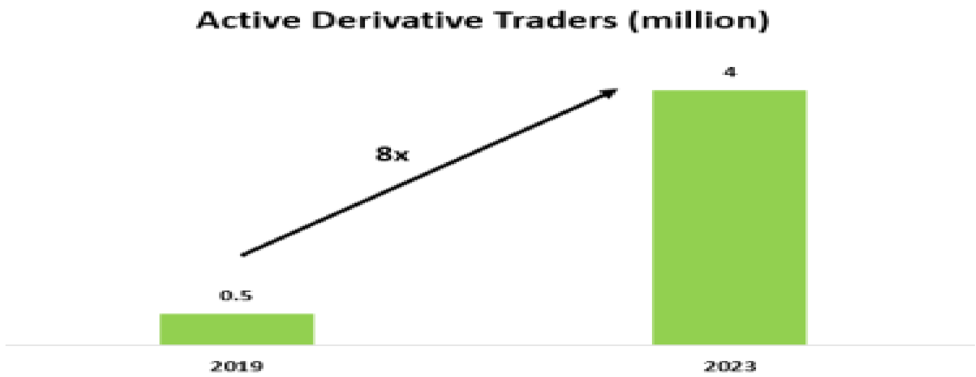

Figure 2: Active Derivative Traders in India

Source: *NSE, BSE, Axis MF Research*

2. AI in Derivative Pricing & Valuation

AI is in rapid use and is slowly being adopted by the financial market for various purposes. Similarly, AI is used in the derivatives market for various purposes like risk assessment, price valuation, hedging optimization, fraud detection, operational risk, and many more. Financial institutions can use AI to predict credit risk and counterparty risk in real-time by analyzing user behavior, credit history, and market transactions (Huang et.al, 2024)). AI can be used in the following models to make pricing, valuation, and risk management processes easier and faster.

2.1 *Black Scholes model*

The Black-Scholes model is a widely recognized and mathematically sophisticated framework for pricing European options, which are financial derivatives that can only be exercised at the time of expiry. Introduced in 1973, it was the first major model for option pricing and significantly influenced the development of modern derivatives markets. The model operates under the assumption that the underlying asset does not distribute dividends during the option's life, and its analytical approach provided an elegant solution to option valuation that has remained relevant and widely applied in contemporary financial markets.

Despite its foundational role, subsequent research—most notably by Rubinstein (1985) and Bates (1996)—has identified several limitations in the Black-Scholes model. These include the presence of the volatility smile, which reflects systematic pricing deviations depending on whether an option is deep in or out of the money; the non-flat term structure of implied volatility, which results in valuation inaccuracies depending on the time to maturity; and the put-call skew, which captures persistent differences in the relative pricing of puts and calls influenced by market dynamics such as trading volume and investor sentiment (Bennell and Sutcliffe, 2004). These empirical anomalies highlight the model's inability to fully account for complex and evolving market conditions.

The integration of artificial intelligence (AI) into option pricing methodologies offers the potential to mitigate such shortcomings. AI techniques are capable of learning from extensive historical and real-time datasets, identifying hidden patterns, and dynamically adapting to changing market environments—capabilities that traditional parametric models such as Black-Scholes inherently lack. Among these, the Artificial Neural Network (ANN) represents a particularly promising approach. Modeled on the structure and functioning of the human brain, ANNs consist of interconnected nodes that process and learn from historical data, enabling them to capture non-linear relationships among key variables and deliver more accurate and efficient pricing outcomes.

Empirical evidence supports the efficacy of this approach. A study by Mary Mallinaris and Linda Solchenberger demonstrates that neural network-based pricing models consistently outperformed the Black-Scholes framework in terms of accuracy. The ANN not only reduced pricing errors but also effectively addressed structural biases inherent in the Black-Scholes model, including the volatility smile, put-call skew, and the non-flat term structure of implied volatility (Malliaris and Salchenberger, 1993). These findings underscore the potential of AI-driven models to enhance option valuation practices by offering greater flexibility, adaptability, and precision in capturing the true dynamics of financial markets.

2.2 *Monte Carlo Simulation*

Monte Carlo Simulation is a quantitative technique that estimates a wide range of potential future outcomes by randomly altering variables such as stock prices, interest rates, or inflation. This process is repeated thousands of times to generate different possible results. Unlike traditional methods that assume a fixed rate of return—which is often unrealistic—Monte Carlo Simulation produces thousands of simulated future market returns based on historical data and calculates the growth of an investment over time for each scenario. The outcome is a probability distribution of potential future values.

Monte Carlo methods are particularly valuable in pricing complex derivatives, as they can model numerous potential market paths. They are especially suited for path-dependent options, multi-asset products, risk sensitivity calculations (Greeks), and stress testing portfolios under extreme market conditions (Quest). Incorporating artificial intelligence (AI) into Monte Carlo Simulation further enhances both accuracy and computational efficiency. Neural networks can accelerate simulations and improve precision, while machine learning enables the model to adapt based on historical data, allowing the simulation to better capture real-world market features. Surrogate AI models can be employed to smooth noise and stabilize simulation results. Furthermore, AI systems can learn from significant historical market events, such as the 2008 financial crisis, and integrate these extreme conditions into Monte Carlo scenarios, thereby improving the robustness of the pricing and risk assessment process.

2.3 *Sentiment analysis*

Sentiment analysis, also known as opinion mining, emotion mining, or subjectivity mining, is a technique used to evaluate investors' emotions, attitudes, opinions, and overall sentiment. It is generally expressed in terms of polarity, which refers to the direction of the sentiments—positive, negative, mixed, or neutral—and can also vary in intensity, for example, slightly good or extremely good (Sonagi and Gore, 2013).

Artificial intelligence (AI) facilitates sentiment analysis through Natural Language Processing (NLP), text mining, and machine learning. NLP enables computers to understand, interpret, and generate human language, allowing machines to read, process, and respond to text or speech in a manner that closely aligns with natural human interaction. The integration of AI into NLP enhances the ability to process large volumes of data quickly and with higher accuracy. Text mining involves examining and extracting meaningful insights from text or voice data, while machine learning—particularly supervised algorithms that utilize labeled datasets—enables systems to learn from historical information and improve performance without explicit reprogramming (Kolchyna *et.al*., 2015). In the context of sentiment analysis, machine learning allows systems to automatically detect, categorize, and quantify emotions embedded in textual data.

Sentiment analysis tools, including social media monitoring systems, opinion mining algorithms, NLP techniques, text mining methods, and machine learning models, have become essential components of modern trading strategies. These tools systematically process large amounts of unstructured textual data from diverse sources such as news articles, blogs, online forums, and social media platforms to determine the prevailing tone and direction of market sentiment. By analyzing variations in language, the frequency of specific financial terms, and the emotional tone in public discourse, such systems quantify whether the overall sentiment is bullish or bearish. This analytical capability provides valuable insights into potential market movements, thereby supporting more informed, timely, and strategic investment decisions.

2.4 *Risk management*

Risk represents the exposure to uncertainty, while risk management encompasses the processes of identifying risk tolerance, measuring potential exposures, modifying positions, monitoring developments, and minimizing adverse outcomes. Effective risk management is indispensable for achieving optimal portfolio performance. Within this framework, derivatives—including swaps, futures, options, and forwards—play a central role in hedging, speculation, and risk transfer (Hammoudeh and McAleer, 2013).

Derivatives function as crucial instruments in contemporary financial markets, enabling investors to manage and mitigate diverse categories of risk. They are extensively employed to hedge against interest rate volatility, safeguarding borrowers and investors from unpredictable shifts in financing costs or investment returns. Similarly, derivatives are essential in managing currency risk, particularly in cross-border trade and investment, where exchange rate fluctuations can materially impact profitability. They also offer a strategic shield against commodity price instability, a critical consideration for enterprises dependent on raw materials. Beyond these applications, derivatives provide mechanisms for anticipating and managing future price changes of various assets, facilitating more stable and strategically aligned portfolio structures. Consequently, derivatives enhance the robustness of risk management frameworks and contribute to overall financial stability.

The integration of Artificial Intelligence (AI) into risk management processes is transforming the speed, accuracy, and adaptability of decision-making in financial markets. Advanced AI methodologies—such as deep learning, neural networks, and reinforcement learning (RL)—allow for highly efficient scenario analysis, enabling rapid assessment of the impact of market shocks, including abrupt interest rate changes, on portfolios containing swaps, options, and other derivatives. This capability facilitates early identification of risk transmission channels and supports timely and targeted hedging strategies. By processing large-scale, complex datasets, AI significantly improves forecasting precision and delivers a more comprehensive understanding of vulnerabilities across a range of market conditions.

AI-driven techniques, including decision tree models and unsupervised learning algorithms, are proving particularly effective in credit risk modeling by uncovering latent patterns and segmenting borrowers according to their risk profiles. Machine learning further enhances fraud detection by processing vast volumes of transactional data to identify anomalies and suspicious activities in real time. Natural Language Processing (NLP) and text mining also serve as powerful analytical tools for monitoring trade behavior, detecting market manipulation, and uncovering potential insider trading through the examination of financial news, regulatory filings, and communication records (KPMG. 2021).

Within structured risk frameworks, AI mitigates operational risk—losses arising from process failures, human error, or system breakdowns—as well as model risk, which stems from flawed assumptions or errors in financial modeling. Reinforcement learning, through its iterative interaction with dynamic market environments, supports adaptive hedging strategies, strengthens operational controls, and enhances trading risk management by responding in real time to evolving market conditions. Additionally, AI refines the assessment of counterparty risk, which reflects the probability of default by a contractual counterparty, and credit risk, representing the likelihood of financial loss when contractual obligations are not fulfilled. By combining predictive modeling, anomaly detection, and adaptive learning, AI facilitates proactive risk identification, improves portfolio resilience, and underpins data-driven decision-making in increasingly complex and interconnected global markets.

2.5 *Machine learning*

Machine learning, a subfield of artificial intelligence, enables computers to learn from historical data and make predictions or decisions without requiring explicit programming for each task. In recent years, its significance in the derivatives market has grown substantially, driven by the increasing complexity and rapid evolution of financial instruments. By enhancing pricing precision, trading efficiency, and risk management capabilities, Machine Learning (ML) is reshaping the way derivatives are analyzed, valued, and traded. A range of ML models—such as neural networks and reinforcement learning—are now applied to improve both the accuracy and the speed of analysis in derivatives trading. These models possess the ability to detect complex, non-linear patterns within large and diverse datasets, adapt to evolving market dynamics, and generate predictive insights that traditional analytical approaches may fail to capture. Consequently, ML has proven highly effective in areas such as risk management, credit risk assessment, fraud detection, algorithmic trading, and portfolio optimization. By processing massive volumes of data rapidly and learning from historical patterns, ML empowers financial institutions to make better-informed decisions and respond more effectively to changing market conditions (Jarunde Nikhil, 2021).

A particularly notable ML application in the derivatives market is Natural Language Processing (NLP), which facilitates the systematic analysis of unstructured textual data, including financial news, corporate filings, analyst reports, and social media content. Through the transformation of qualitative market narratives into quantifiable sentiment indicators and event-driven signals, NLP enables the integration of real-time market sentiment into pricing models and hedging strategies, thereby enhancing responsiveness to emerging developments. Complementing NLP, advanced ML architectures—particularly Artificial Neural Networks (ANNs) and Deep Neural Networks (DNNs)—are redefining derivative valuation methodologies. Inspired by the structure of the human brain, these networks consist of interconnected computational layers capable of modeling intricate dependencies between variables such as underlying asset prices, implied volatility surfaces, interest rates, and macroeconomic indicators. Unlike conventional closed-form pricing models, ANNs and DNNs learn directly from both historical and streaming market data, enabling dynamic adaptation to shifting market conditions. This adaptability, combined with their capacity to approximate complex pricing functions with high precision, results in faster computations, reduced model error, and greater resilience under volatile or non-stationary environments. As a result, ML has emerged as an indispensable analytical and operational tool in the modern derivatives landscape, offering both strategic and tactical advantages in an increasingly data-driven financial ecosystem.

3. The Indian Scenario: AI in Derivatives Trading

Figure 3: India's Derivative Turnover

Source: Bloomberg

Derivative trading in India has experienced substantial growth in recent years, a trend that accelerated notably after the COVID-19 pandemic. Historically, traders have relied on established valuation and pricing methodologies, including the binomial option pricing model, Monte Carlo simulation, put–call parity, the Garman–Kohlhagen model, among others. These traditional frameworks have provided a structured basis for derivative pricing; however, the rapid advancement of artificial intelligence (AI) has begun to redefine the landscape.

Recent innovations in AI have significantly transformed the dynamics of derivatives trading by enabling models that process large datasets, adapt to evolving market conditions, and deliver predictions with greater speed and accuracy than conventional approaches. In the Indian context, this technological shift is evident in the growing dominance of algorithmic trading, which now accounts for approximately 60–70% of total trading volume. Market participants increasingly employ diverse AI methodologies—including supervised learning, unsupervised learning, reinforcement learning, deep learning, and natural language processing (NLP)—to detect intricate market patterns, identify arbitrage opportunities, and execute trades with minimal latency.

In recognition of these developments, the Securities and Exchange Board of India (SEBI) has introduced a draft regulatory framework aimed at ensuring the responsible adoption of AI in the derivatives market. Built upon five key pillars—governance, transparency, fairness, data security, and risk management—the framework mandates prior approval of all AI-based algorithms by stock exchanges. Each order generated by such algorithms must carry a unique identifier to enable traceability and facilitate robust audit processes. Furthermore, the framework extends participation to technologically adept individual investors, allowing them to register their algorithms through authorized brokers.

Through these measures, SEBI seeks to strike a balance between fostering technological innovation and safeguarding investor interests, thereby enabling the Indian derivatives market to integrate AI responsibly while aligning with global regulatory practices. Although India continues to lag behind advanced economies such as the United States and the United Kingdom in AI adoption, algorithmic trading infrastructure, and advanced analytics, the domestic market is nonetheless witnessing gradual yet steady technological progress. Ongoing initiatives by regulators, financial institutions, and technology providers—spanning predictive analytics, automated execution systems, and AI-driven risk management—signal a clear trajectory toward a more technology-oriented derivatives ecosystem, albeit with a persistent gap relative to global leaders.

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