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AI Driven Financial Market Volatility Predictor Using Real Time Data

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Abstract:
Financial market volatility is a critical factor influencing global investment strategies, with fluctuations leading to losses exceeding $1 trillion annually. The International Monetary Fund (IMF) reports that volatility can double the cost of equity capital, negatively impacting business growth and financial stability. Traditional volatility prediction methods rely heavily on historical data and static models, which often fail to capture the dynamic nature of financial markets. To address these challenges, this study proposes an AI-driven approach that utilizes deep learning classification techniques for real-time financial market volatility prediction. The proposed system improves predictive accuracy through robust data preprocessing, including normalization and feature selection, ensuring high-quality inputs for the models. The CNN model, with its ability to extract intricate patterns from data, offers superior classification performance compared to traditional machine learning models. The KNN model is used as a benchmark, providing insights into the effectiveness of deep learning techniques in handling market fluctuations. Beyond predicting market volatility, the model focuses on customer churn prediction, classifying customers as "Churn" or "Not Churn" to assist financial institutions in risk management and customer retention. Since customer retention is more cost-effective than acquiring new customers, analyzing attributes like credit score, geography, gender, age, tenure, balance, number of products, and activity status helps identify churn patterns. By integrating KNN and CNN models, this study provides a comparative analysis of traditional and deep learning methods, demonstrating the potential of AI-driven systems in financial forecasting. The framework enhances risk assessment and strategic decision-making, ensuring a more reliable and efficient approach to market volatility prediction.

1. INTRODUCTION

Financial market volatility plays a critical role in investment decision-making, economic policy formulation, and risk management. In India, stock market fluctuations significantly impact investors, businesses, and the overall economy. For instance, the Bombay Stock Exchange (BSE) Sensex saw a drastic decline of nearly 40% in early 2020 due to the COVID-19 pandemic, leading to massive investor losses. The National Stock Exchange (NSE) has also experienced frequent periods of high volatility, driven by factors such as global economic uncertainty, inflation, and regulatory changes. Traditional volatility prediction methods rely on statistical models like GARCH and ARCH, which often fail to capture rapid fluctuations in real-time. With the rise of artificial intelligence (AI) and deep learning, financial institutions can leverage real-time data to enhance prediction accuracy and mitigate risks. AI-driven models process vast amounts of data from stock trends, investor sentiment, and macroeconomic indicators, providing timely insights to traders, policymakers, and financial analysts. The proposed system integrates deep learning techniques with real-time bank customer data, classifying customers into "Stable" or "Not Stable" groups, helping financial institutions assess risk, optimize investment strategies, and enhance customer retention.

2. LITERATURE SURVEY

Traders can use accurate forecasts to make more informed decisions about when to enter and exit positions in financial markets. For instance, the low volatility during the summer of 2022 have caused traders large losses and stresses the importance of high conviction of volatility movements Tsekova & Popina, [1]. Finally, governments and institutions can benefit from accurate volatility forecasts to assess the volatility and its impacts on the economy to make effective policy decisions regarding monetary and regulatory policy. Over the last couple of years, there have been several literature reviews which study various deep learning-based neural network approaches for stock market forecasting, which mainly focuses on stock price prediction Jiang et al.,[2] while studies financial time series forecasting in general, using deep learning.

2.Henrique et al.,[3] focus on machine learning approaches for various financial market predictions. Furthermore, Bustos and Pomares-Quimbaya et al.,[4] focus on stock market movement prediction.

either minor part of the scope, or not present. Poon and Granger et al.,[5] conducted an early review concerning volatility forecasting in financial markets, but due to the more recent popularity and boom within machine learning and artificial intelligence, such approaches are not considered in that review. The selected databases are Web of Science, Scopus, Science Direct and ProQuest, which are among the largest and more commonly used for such database-driven searches. By conducting searches through multiple multi-publisher databases most publications from publisher-specific sources will also be included

Hiebl, et al.,[6].

3.Some composite indices in this category consists of assets outside of the US, but for simplicity they will be classified based on the index' country of origin. Eight studies used commodities, six of which were oil. These were primarily based on WTI indices, but Tissaoui et al.

[7] focused their study on the OVX. As these are all based on American assets, they were placed into the American market. However, there are some benefits to approaching more localized markets, especially if measured against the larger indices. It might aid in discovering local differences, in turn allowing for a deeper understanding of the drivers of volatility. Additionally, some localized assets might exhibit different behavior compared to the larger counterparts, as shown by Chen and Hu [8].

4.Of the remaining ten papers, two applied technical indicators based on their respective asset of choice: Petrozziello et al.,[9] provided their LSTM with open-close returns in addition to the realized volatility estimate, converted volatility into five technical indicators. Generally, its ability to handle multicollinearity and non-linearity in a data-driven way makes it an attractive option for including exogenous data.

5.This was demonstrated by Christensen et al.,[10], where increasing the forecasting horizon severely improved the performance of RF over econometric models when including external data.

Similarly, Higashide et al. [11] based their research on high frequent financial and technical data – such as trading volume and bid–ask spreads – accessible at an intradaily frequency. Some authors also applied two different sampling schemes.

6.Prasad et al. [12] used both daily and weekly macroeconomic variables to forecast the corresponding direction of the VIX, where the weekly data was included due to reporting delays for daily data. In recent decades, volatility forecasting has been one of the most active areas in time-series econometrics and financial data mining.

7.Effective forecasting is of great importance for many financial activities, such as risk management Dvorsky et al., [13], option pricing Kim et al., [14], and portfolio optimisation Lampariello et al., [15]. Unlike other time-series applications, there are many unpredictable influences on financial volatility, such as political events, investors' psychology, and market information asymmetry. Moreover, how to accurately forecast the fluctuation or tendency of the Stock Index has become an urgent issue for investors and policy-makers. Hence, studying the volatility of the Stock Index is imperative.

3. PROPOSED METHODOLOGY

Step 1: Churn Dataset

The user begins by uploading a dataset containing information related to financial transactions and customer details, typically a churn dataset, using a file dialog.

Step 2: Data Preprocessing

basic information about the dataset is displayed (e.g., null values, data summary). Label encoding is applied to categorical columns like "Gender," "Geography," and "Surname." Unnecessary columns are removed, missing values are handled, and the dataset is cleaned of duplicates and NaNs. The data is resampled to handle class imbalance, ensuring balanced target classes for prediction. The dataset is then split into training and test sets.

Step 3: Exploratory Data Analysis (EDA) Plots

Various visualizations are generated, such as a count plot to analyze the distribution of classes, and a correlation heatmap for understanding relationships between different features.

Step 4: Existing KNN Classifier

A K-Nearest Neighbors (KNN) classifier is trained using the preprocessed data. If a trained model already exists, it's loaded and used for predictions; otherwise, a new KNN model is trained, evaluated, and saved. Metrics such as accuracy, precision, recall, and F1-score are calculated and displayed.

Step 5: Proposed CNN Classifier

A Convolutional Neural Network (CNN) is proposed for improved performance. The model consists of multiple convolutional layers, dropout layers, and dense layers. The model is trained, evaluated, and saved. Additionally, a Random Forest Classifier (RFC) is used to train on features extracted from the CNN model to enhance classification.

Step 6: Performance Comparison Graph

The performance of both the KNN and CNN classifiers is compared visually using a bar chart displaying accuracy, precision, recall, and F1-score for each model.

Applications:

LIME's enhanced images can be used in a wide range of applications , including:

- Surveillance systems (improving nighttime video quality)
- Astrophotography (capturing stars and galaxies in low-light conditions),
- Consumer photography (improving smartphone camera performance in dimly lit environments).

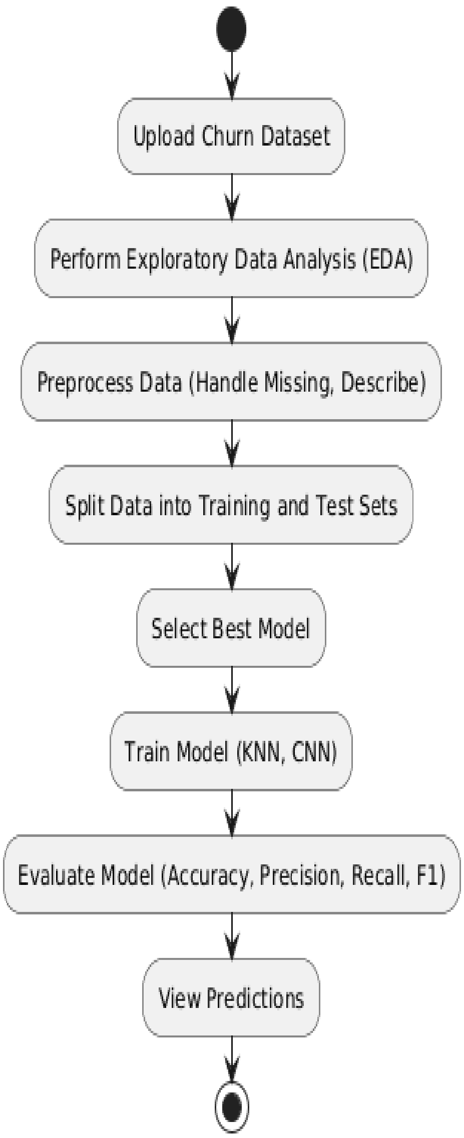
Advantages:

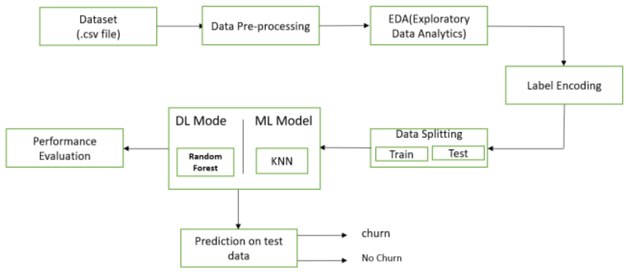
LIME is a technique that leverages deep learning and image processing to enhance images captured in low-light conditions. It offers several advantages, making it a valuable solution for various applications:

- Improved Visibility: LIME significantly improves the visibility of images captured in low-light environments. It enhances details, enhances contrast, and brightens dark areas, making objects and features more discernible.

- Reduced Noise: LIME includes noise reduction mechanisms, which help in reducing the noise present in low-light images. This results in cleaner and more visually appealing images.
- Enhanced Details: The algorithm preserves and enhances fine details in the image, which is crucial for applications like surveillance, where capturing intricate details is essential.
- Customization: LIME often provides parameters that allow users to customize the enhancement process. Users can adjust parameters such as the strength of enhancement, gamma correction, and more to achieve the desired visual effect.
- Automatic Enhancement: While customization is available, LIME can also operate with default settings, making it suitable for users who may not have expertise in image processing.
- Realism: LIME's enhancements are designed to maintain the natural and realistic appearance of the scene. It avoids over-processing that can result in unnatural-looking images.
- Quality Metrics: The algorithm often includes the calculation of image quality metrics like PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index), allowing users to objectively measure the improvement in image quality.

Versatility: LIME is versatile and applicable in various domains, including surveillance, consumer photography, asonomy, medical imaging, and more. It addresses the common challenge of low-light conditions in these fields.





4.EXPERIMENTAL ANALYSIS

1. Traditional Agricultural

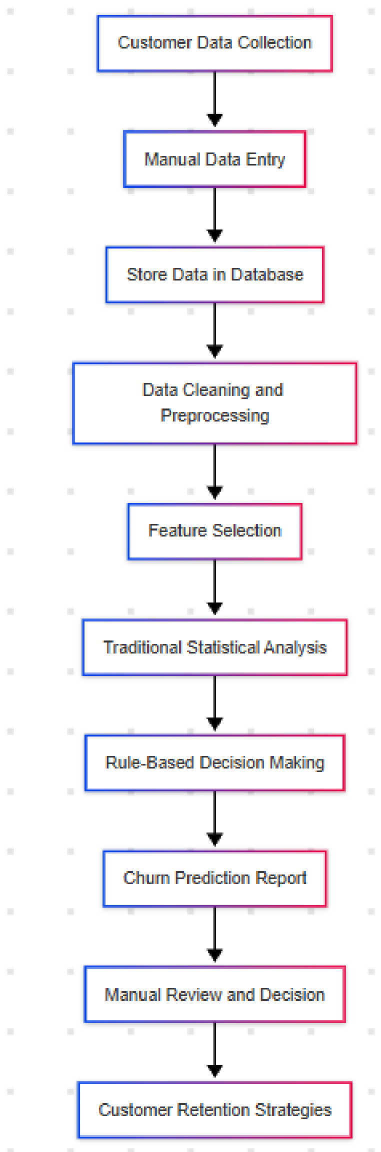
Before the advent of machine learning and AI-driven approaches, financial market volatility prediction primarily relied on statistical and econometric models. Some of the most commonly used traditional methods include:

- **ARCH (Autoregressive Conditional Heteroskedasticity) & GARCH (Generalized ARCH) Models** – These statistical models estimate volatility based on historical price fluctuations.
- **Exponential Moving Average (EMA) & Simple Moving Average (SMA)** – Used to smooth out price data and detect trends over time.
- **Monte Carlo Simulations** – Used for risk assessment by generating multiple possible market scenarios.
- **Value at Risk (VaR) Models** – Estimate potential losses **Fundamental & Technical Analysis** – Involves analyzing financial statements, market trends, and price movements.
- **Econometric Models (e.g., CAPM, Fama-French)** – Used to estimate expected returns and assess risk factors.

2. Limitations

- **Dependence on Historical Data** – Most traditional models rely solely on past market behavior, making them ineffective in capturing sudden shifts in market conditions.
- **Lack of Real-Time Adaptability** – These models cannot efficiently process real-time data, limiting their ability to provide timely predictions.
- **Assumption-Based Models** – Many statistical techniques operate under rigid assumptions (e.g., normal distribution of returns), which do not always hold true in real-world financial markets.
- **Inability to Process Unstructured Data** – Traditional models struggle to incorporate alternative data sources like news sentiment, social media trends, or global economic indicators.

- **Limited Accuracy in High Volatility Periods** – During financial crises or major economic events, traditional methods often fail to provide reliable forecasts.
- **Computational Complexity** – Some econometric models require extensive manual adjustments and fine-tuning, making them resource-intensive and less scalable.
- **Lack of Personalization** – Traditional approaches do not consider individual investor behavior or customer-specific data, limiting their application in risk assessment.
- **Inflexibility in Changing Market Conditions** – Static models do not adapt to evolving financial trends, reducing their predictive effectiveness over time.



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