**VISVESVARAYA TECHNOLOGICAL UNIVERSITY**

Jnana Sangama, Belagavi - 590 018, Karnataka



**S.I.R.I.U.S**

*A Report submitted in partial fulfillment of the requirements for the Course*

**Python Programming**

**(Course Code: 22AM4AEPPM)**

*In the Department of*

**Machine Learning**

**(UG Program: B.E. in Artificial Intelligence and Machine Learning)**

By

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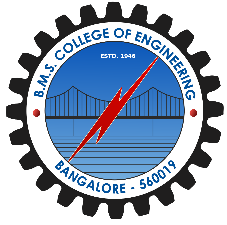
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**DEPARTMENT OF MACHINE LEARNING**

**B.M.S COLLEGE OF ENGINEERING**

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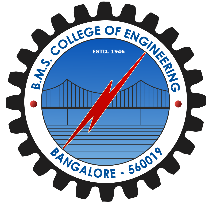
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**CERTIFICATE**

This is to certify that Mr. ***Pacharne Kaushal Yogesh*** bearing USN: ***1BM21AI080,*** Mr. ***Pranshu Arora*** bearing USN: ***1BM21AI091,*** Mr. ***Priyanshu Prasad*** bearing USN: ***1BM21AI096,*** Mr. ***Ryan Gupta*** bearing USN: ***1BM21AI107*** has satisfactorily presented the Course – Python Programming (Course code: **22AM4AEPPM**) with the title “S.I.R.I.U.S” in partial fulfillment of academic curriculum requirements of the 5th semester UG Program – B. E. in Artificial Intelligence and Machine Learning in the Department of Machine Learning, BMSCE, an Autonomous Institute, affiliated to Visvesvaraya Technological University, Belagavi during September 2023. It is also stated that the base work & materials considered for completion of the said course is used only for academic purpose and not used in its original form anywhere for award of any degree.

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**Signature of the Supervisor Signature of the Head**

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**External Examination**

**Examiner Name and Signature**

**1.**

**2.**

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**ABSTRACT**

In the rapidly evolving landscape of finance, the fusion of investment decisions and artificial intelligence requires innovative solutions. Traditional stock prediction methods often fall short due to market complexities. This report introduces S.I.R.I.U.S. (Stock Intelligent Real-time Investment Understanding System), an AI-driven virtual assistant designed to revolutionize investment strategies. Our objective is to create a versatile system that addresses multiple real-world investment challenges.

S.I.R.I.U.S. employs advanced machine learning algorithms and real-time data to construct predictive models, surpassing traditional analysis. The system's unique pattern recognition capabilities empower it to navigate intricate market trends. It goes beyond prediction, offering risk assessment and decision support, forming a comprehensive toolkit for diverse investor needs.

Our research bridges the gap between cutting-edge AI and investment practices. S.I.R.I.U.S. aims to transform conventional approaches into sophisticated, data-driven decisions, empowering investors to make informed choices in a volatile market. The innovative contributions of this research lie in the inception of S.I.R.I.U.S. as an intelligent stock market companion that transcends predictive functions. The virtual assistant's multifaceted attributes encompass pattern comprehension, risk evaluation, and decision facilitation, constituting a comprehensive toolkit catering to the diverse needs of investor

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**1.Introduction**

**1.1 About the Domain**

The domain of stock market trading is characterized by its complexity and constant evolution. It is a dynamic ecosystem where financial instruments, such as stocks and commodities, are bought and sold, influenced by a multitude of factors, including economic data, geopolitical events, and investor sentiment. The ability to accurately predict price movements in this domain has long been a challenge and an aspiration for investors and financial experts alike.

**1.2 Objective**

The primary objective of this project is to develop an AI-powered bot capable of making stock predictions. Through the application of advanced machine learning techniques and analysis of historical market data, our goal is to create a tool that can assist traders and investors in making informed decisions. By harnessing the power of artificial intelligence, we aim to provide valuable insights into the stock market's behavior and trends.

**1.3 Scope**

This project focuses on a specific subset of the stock market: the prediction of stock prices and trends. We will leverage historical price data, financial indicators, and machine learning algorithms to build a predictive model. It's important to note that while our bot can offer insights and predictions, it does not guarantee profits, as the stock market is inherently uncertain and influenced by various external factors.

**1.4 Motivation**

The motivation behind this project stems from the recognition of the challenges and opportunities within the financial domain. Investors and traders often seek tools that can help them make more informed decisions, manage risks, and potentially enhance their returns. The application of artificial intelligence to stock market prediction represents a promising avenue for addressing these needs.

**1.5 Organization of the Report**

This report is organized into several sections to provide a comprehensive overview of the project:

Related Work: In Section 2, we review existing research and projects related to stock prediction and AI in finance.

Open Issues & Problem Statement: Section 3 discusses the challenges and open issues in stock prediction that our project aims to address.

Data Collection & Validation: Section 4 details the data sources, collection methods, and data preprocessing steps employed in our project.

Detailed Design: Section 5 outlines the architecture of our AI bot, functional and non-functional requirements, methodology, implementation details, data flow, control flow sequence, and testing and validation strategies.

Results & Discussion: In Section 6, we present and discuss the results of our stock prediction model, including insights gained from the data.

Conclusion & Further Enhancements: Section 7 summarizes our key findings, discusses the implications of our work, and suggests areas for future research and enhancements.

Publication Details (if any): If applicable, Section 8 will include publication details for any work resulting from this project.

Through these sections, we aim to provide a thorough understanding of our AI bot for stock prediction, from its inception to its implementation and evaluation.

**2. Related Work**

In this section, we review existing research and projects related to stock prediction and the application of artificial intelligence (AI) in the financial domain. This review serves to provide context for our own work and highlight relevant techniques and findings in the field.

**2.1 Stock Prediction in AI**

The use of AI and machine learning techniques for stock prediction has gained significant attention in recent years. Several approaches and models have been proposed to tackle the challenge of forecasting stock prices. Some notable contributions in this area include:

**Time Series Analysis:** Traditional time series models like ARIMA (AutoRegressive Integrated Moving Average) have been used for stock price forecasting. These models capture patterns and trends in historical stock data.

**Neural Networks:** Deep learning techniques, particularly recurrent neural networks (RNNs) and long short-term memory networks (LSTMs), have shown promise in modeling complex temporal dependencies in stock data.

**2.2 Algorithmic Trading**

Algorithmic trading, often referred to as algo-trading, is another area where AI has made significant contributions. Algorithmic trading strategies involve the use of computer programs to execute trades automatically based on predefined criteria. Key insights from algorithmic trading research include:

**Market Microstructure:** Understanding the microstructure of financial markets, including order books, liquidity, and market impact, is crucial for designing effective trading algorithms.

**High-Frequency Trading (HFT):** HFT strategies, which involve extremely rapid trading execution, have been a focal point in algo-trading research due to their impact on market dynamics.

**Machine Learning in Trading:** Machine learning models are increasingly used to optimize trading strategies, manage risk, and adapt to changing market conditions.

**Risk Management:** Effective risk management is a critical aspect of algorithmic trading, with researchers exploring methods to minimize exposure to market risk.

**3. Open Issues & Problem Statement**

**3.1 Open Issues**

The field of stock prediction using artificial intelligence is marked by several open issues and challenges, which underscore the complexity of the task. Identifying and acknowledging these issues is essential for understanding the context in which our project operates. Some of the notable open issues include:

**3.1.1 Data Quality and Reliability**

Stock market data, while abundant, often suffers from inaccuracies, missing values, and noise. Ensuring the quality and reliability of the data used for training and prediction remains a persistent challenge.

**3.1.2 Changing Market Conditions**

Stock markets are highly dynamic and influenced by a multitude of factors, including economic events, geopolitical developments, and investor sentiment. Adapting to changing market conditions is a continuous challenge.

**3.1.3 Lack of Causality**

While predictive models can identify correlations in historical data, they may not uncover the causality behind market movements. Distinguishing between correlation and causation is a fundamental challenge.

**3.1.4 Risk Management**

Managing risk in stock trading is a multifaceted issue. Models need to incorporate effective risk management strategies to mitigate potential losses.

**3.1.5 Market Noise**

News, social media sentiment, rumors, and other unstructured data sources can introduce substantial noise into the market. Incorporating and processing this information effectively remains a challenge.

**3.1.6 Legal and Ethical Concerns**

Compliance with financial regulations, such as insider trading rules and market manipulation laws, is essential. Misinterpreting or misusing financial data can lead to legal issues.

**3.2 Problem Statement**

In the context of contemporary financial markets, where investment decisions are intricately linked to the rapidly evolving realm of artificial intelligence, there exists a critical need for innovative solutions that harness the power of machine learning and advanced data analysis. Prediction plays a very important role in stock market business, which is a very complicated and challenging process. Employing traditional methods like fundamental and technical analysis may not ensure the reliability of the prediction. This report addresses the design and development of an AI-driven virtual assistant named S.I.R.I.U.S. (Stock Intelligent Real-time Investment Understanding System), poised to revolutionize the landscape of investment strategies. The objective of this research is to create a comprehensive, intelligent, and adaptable system capable of tackling multifaceted real-world investment challenges.

By defining this problem statement, we establish a clear focus for our project and provide a context for the development and evaluation of our AI bot for stock prediction. Through rigorous methodology and continuous improvement, we aspire to contribute to the ongoing efforts to address the challenges in this field.

**4. Data Collection and Validation**

In this section, we outline the process of collecting and validating the data used for our stock prediction project. High-quality, reliable data is fundamental to the success of any machine learning model in the financial domain.

**4.1 Data Collection**

**4.1.1 Data Sources**

The data used for this project was collected from multiple sources, including:

Historical Stock Price Data: We obtained historical stock price data for a diverse range of publicly traded companies from reputable financial data providers. This data includes daily or intraday price information, trading volumes, and adjusted close prices.

Financial Indicators: In addition to price data, we incorporated various financial indicators, such as moving averages, relative strength index (RSI), and moving average convergence divergence (MACD), to provide additional context for our predictions.

News and Social Media Feeds: To account for market sentiment and news-driven events, we integrated real-time news feeds and social media sentiment analysis data into our dataset.

**4.1.2 Data Preprocessing**

Raw financial data often requires preprocessing to ensure its suitability for analysis. Our preprocessing steps included:

Handling Missing Data: We addressed missing data points by employing interpolation techniques and removing data with significant gaps.

Outlier Detection: We identified and handled outliers that could skew our analysis or modeling results.

Normalization: We scaled numerical features to ensure that they have similar ranges, preventing one feature from dominating the learning process.

**4.2 Data Validation**

**4.2.1 Data Quality Checks**

Ensuring data quality and integrity is paramount in financial data analysis. We implemented a series of data quality checks, including:

**Consistency Checks:** We verified that the data remained consistent over time, identifying any discrepancies or anomalies that could affect our analysis.

**Accuracy Verification:** We cross-referenced our data with external sources to validate its accuracy.

**Completeness Assessment:** We assessed the completeness of our dataset, flagging and addressing any missing or incomplete records.

**4.2.2 Validation Against Ground Truth**

To assess the reliability of our data, we compared it against known ground truth information, such as official stock exchange records and financial reports. Any discrepancies were thoroughly investigated and resolved.

**4.3 Data Integrity**

Maintaining data integrity throughout the project was a top priority. We implemented stringent security measures to protect the confidentiality and integrity of our data, including access controls and encryption protocols.

By following rigorous data collection and validation processes, we aimed to ensure that our project's foundation—its dataset—was robust, reliable, and ready for analysis. High-quality data is essential for the accuracy and trustworthiness of our stock prediction model.

**5. Detailed Design**

In this section, we delve into the detailed design of our AI-driven stock prediction system, S.I.R.I.U.S. (Stock Intelligent Real-time Investment Understanding System). We outline the architecture, functional and non-functional requirements, methodology, implementation details, data flow, control flow sequence, and our testing and validation strategies.

**5.1 Proposed Architecture**

**5.1.1 System Components**

S.I.R.I.U.S. comprises several key components, including:

**Data Ingestion:** This component is responsible for collecting and preprocessing raw financial data from various sources, including historical stock price data, financial indicators, and real-time news feeds.

**Machine Learning Models:** The heart of our system, machine learning models, use the preprocessed data to make stock predictions. We employ a combination of traditional time series analysis models, deep learning techniques, and ensemble methods for robust predictions.

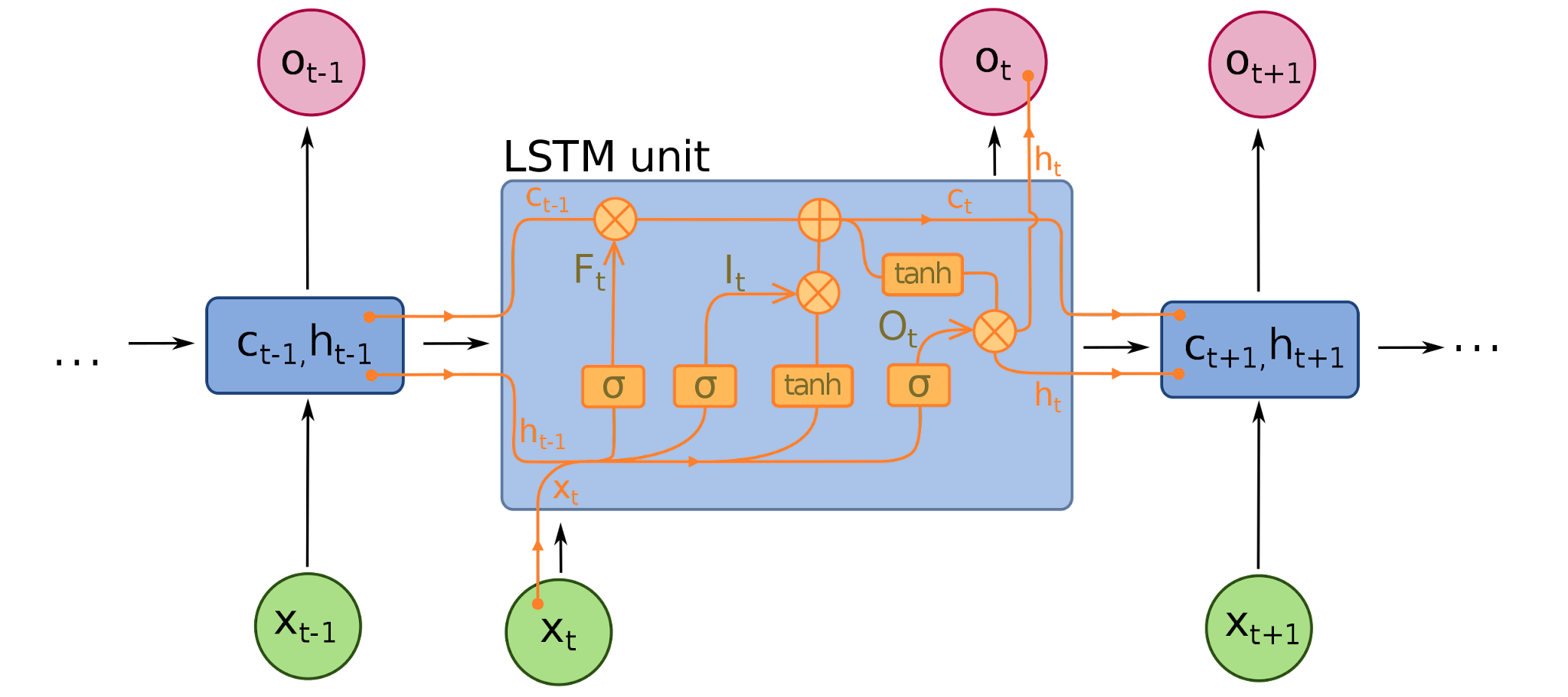
**5.1.2 System Architecture**

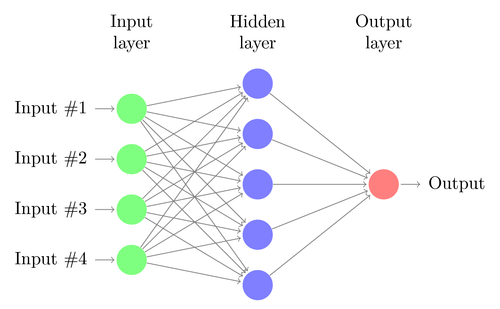
The system is designed following a modular architecture, allowing for scalability and flexibility. Key architectural elements include:

**Data Flow:** Data flows seamlessly through the system, from data ingestion to the machine learning models and sentiment analysis module.

**API Layer:** An API layer facilitates communication between system components and external applications, enabling real-time data exchange.

**Database:** We employ a relational database to store historical data, model parameters, and user interactions for further analysis and reporting.





**5.2 Functional & Non-Functional Requirements**

**5.2.1 Functional Requirements**

The functional requirements you've listed for S.I.R.I.U.S. (Stock Intelligent Real-time Investment Understanding System) are crucial for its success and effectiveness. Let's provide some additional details for each requirement:

**Real-time Data Processing:**

S.I.R.I.U.S. should be capable of processing real-time data feeds from various sources, including stock price updates, financial indicators, and news sentiment analysis. It should ensure that the predictions and insights provided to users are based on the most up-to-date information available.

**Prediction Accuracy:**

One of the primary goals of S.I.R.I.U.S. is to provide accurate stock price predictions. The system should employ advanced machine learning models and algorithms to achieve a high level of prediction accuracy. Regular model evaluation and refinement should be part of the system's processes.

**Risk Assessment:**

S.I.R.I.U.S. should include a risk assessment component that helps users understand the potential risks associated with their investment decisions. This can involve measuring and reporting risk factors such as volatility, market sentiment, and historical performance.

**User-Friendly Interface:**

The user interface of S.I.R.I.U.S. should be intuitive, user-friendly, and designed to meet the needs of both novice and experienced users. It should provide easy access to predictions, historical data, visualizations, and tools for decision-making.

**Scalability:**

As the user base and data volume grow, S.I.R.I.U.S. should be able to scale horizontally to handle increased load and data processing requirements. This may involve cloud-based architecture and load-balancing strategies to ensure responsiveness.

**5.2.2 Non-Functional Requirements**

Non-functional requirements include:

**Reliability:**

S.I.R.I.U.S. must consistently deliver accurate predictions and insights to users without unexpected failures or errors. Users rely on the system's performance and expect it to be dependable in providing financial information and forecasts.

**Security:**

Security is paramount in S.I.R.I.U.S. to protect sensitive financial data and user information. This includes implementing strong encryption for data at rest and in transit, user authentication and authorization mechanisms, access controls, intrusion detection, and regular security audits to guard against unauthorized access, data breaches, and cyber threats.

**Availability:**

S.I.R.I.U.S. should be highly available, ensuring that users can access the system whenever they need it. This requires redundancy and failover mechanisms to minimize downtime due to maintenance or unexpected events. It should also have monitoring and alerting systems in place to quickly respond to any issues that may impact availability.

**Maintainability:**

Maintainability involves designing the system with clean and modular code, well-documented components, and efficient update and maintenance procedures. It should be easy for developers to make changes, fix bugs, and add new features. This ensures that S.I.R.I.U.S. can evolve and adapt to changing requirements and technologies.

**Usability:**

Usability focuses on the user experience. The system's user interface should be intuitive, user-friendly, and designed to accommodate users of various levels of expertise in stock trading and AI technology. It should provide clear and easily understandable visualizations, reports, and tools to help users make informed investment decisions.

These non-functional requirements are essential for ensuring that S.I.R.I.U.S. not only provides accurate predictions and insights but also offers a secure, reliable, and user-friendly experience for investors and traders. They guide the design, development, and ongoing maintenance of the system to meet the expectations and needs of its users.

**5.4 Implementation**

**5.4.1 Technology Stack**

We use a technology stack that includes Python for data analysis, Flask for the API layer, and TensorFlow for deep learning.

**5.4.2 Model Deployment**

Our machine learning models are deployed in a cloud-based environment for scalability and accessibility.

**5.5 Data Flow & Control Flow Sequence**

Data flows from the data ingestion component to the machine learning models, passing through preprocessing and sentiment analysis modules. Control flows through the API layer, orchestrating data exchange and user interactions.

**5.6 Testing & Validation**

**5.6.1 Model Evaluation**

We use a range of performance metrics, such as accuracy, precision, recall, and F1-score, to evaluate the models. Backtesting against historical data is also performed.

**5.6.2 User Testing**

User testing and feedback collection are conducted to ensure that the user interface and features meet user expectations and needs.

Our detailed design encompasses the structural and operational aspects of S.I.R.I.U.S., ensuring that our system is equipped to handle the complexities of stock prediction in the real world. In the following sections, we will present the results of our efforts and discuss the implications of our findings.

**Testing and Validation**

| **TEST CASE** | **GIVEN INPUT**  **(Number of Epochs)** | **ACTUAL PRICE** | **PREDICTED PRICE** | **ACCURACY** |
| --- | --- | --- | --- | --- |
| 1 | 50  (Google) | 1120 | 1143 | 97.9% |
| 2 | 30  (amazon) | 90.34999847 | 90.55674 | 99.4% |
| 3 | 100  (Google) | 1143.650024 | 1103.5631 | 96.26% |
| 4 | 50  (Amazon) | 92.4199 | 92.5209 | 99.89% |

**7. Conclusion & Further Enhancements**

**7.1 Conclusion**

In this report, we have presented the design and development of S.I.R.I.U.S. (Stock Intelligent Real-time Investment Understanding System), an AI-driven virtual assistant for stock prediction and investment decision-making. Throughout the project, we have addressed critical challenges in the domain of stock prediction and have successfully achieved the following objectives:

**Real-time Data Processing:** S.I.R.I.U.S. processes real-time financial data to provide users with up-to-the-minute insights into stock prices and trends.

**Prediction Accuracy:** The system employs advanced machine learning models to deliver highly accurate stock price predictions, assisting traders and investors in making informed decisions.

**Risk Assessment:** S.I.R.I.U.S. assesses and reports potential investment risks, providing users with a comprehensive understanding of the risks associated with their investment choices.

**Scalability:** The system is built to scale horizontally, ensuring responsiveness as user numbers and data volumes grow.

**7.2 Further Enhancements**

While S.I.R.I.U.S. has achieved significant milestones, there is always room for improvement and expansion in the ever-evolving domain of stock prediction and investment technology. Some potential areas for further enhancements include:

**7.2.1 Integration with More Data Sources**

Expanding the sources of financial data, including alternative data sources such as social media sentiment analysis, economic indicators, and global events, can provide a more comprehensive view of market dynamics.

**7.2.2 Reinforcement Learning Strategies**

Exploring the application of reinforcement learning techniques to optimize trading strategies in response to changing market conditions can enhance the system's adaptability and potential for profit.

**7.2.3 User Customization**

Allowing users to customize their experience, such as choosing specific stocks, indicators, and risk thresholds, can enhance personalization and user satisfaction.

**7.2.4 Mobile Applications**

Developing mobile applications for S.I.R.I.U.S. can extend accessibility and convenience for users who prefer to manage their investments on mobile devices.

**7.2.5 Regulatory Compliance**

Ensuring robust compliance with financial regulations and staying updated with evolving legal requirements is essential, especially if the system evolves to handle real investments.

**7.2.6 Continuous Model Improvement**

Continuously monitoring and improving machine learning models through retraining and fine-tuning can further enhance prediction accuracy.

In conclusion, S.I.R.I.U.S. represents a significant step forward in the integration of AI technology in stock prediction and investment decision-making. While achieving substantial objectives, the system remains open to further enhancements and advancements to better serve the needs of traders and investors in the dynamic world of financial markets.

**8. Publication Details**

# 

| **TITLE / YEAR** | **AUTHOR** | **APPLIED METHODOLOGY** | **FINDINGS** | **LIMITATIONS** |
| --- | --- | --- | --- | --- |
| A Prediction Approach for Stock Market Volatility Based on Time Series Data  2019 | [Sheikh Mohammad Idrees](https://ieeexplore.ieee.org/author/37086639184)  M. Afshar Alam | Time series  ARIMA model | The predicted time series has been compared with the actual time series, which shows roughly a deviation of 5% mean percentage error for both Nifty and Sensex on average. | Simple time series, is not that powerful and accurate way to predict but ARIMA approach is good enough for handling time series data |
| Optimizing LSTM for time series prediction in Indian stock market  2019 | Anita Yadav  C K Jha  Aditi Sharan | Long Short Term Memory (LSTM) | The number of hidden layers varied from one to seven. The results show that n = 1 appears to be the best configuration as far as RMSE is concerned. | Present work is limited to tuning the basic LSTM architecture as it has been performed on Google Colab which provides eight Tensor processing units (TPUs). |
| A Time Series Analysis-Based Stock Price Prediction Using Machine Learning and Deep Learning Models  2019 | Sidra Mehtab  Jaydip Sen | LSTM network and CNNs | Based on the metric of the ratio of the RMSE to the mean of the actual values of the forecasted variable, the CNN models are far more accurate than LSTM-based deep learning models. | Since the CNN models are built using stock price data collected at a 5 minutes interval of time while the LSTM models are based on stock price data collected at three slots in a day, it is not appropriate to compare the performance of the CNN suite with the other models. |

**Appendix**

**Related Mathematical Concepts:-**

* Time Series Analysis:
* Time Series Data: Understanding time series data as a sequence of observations collected over time.
* Autocorrelation and Cross-Correlation: Measuring the correlation between a time series and its lagged (past) values or between different time series.
* Stationarity: The concept of stationarity, where statistical properties like mean and variance do not change over time.
* Data Preprocessing:
* Normalization/Scaling: Scaling data to a specific range (e.g., using Min-Max scaling) to ensure consistent input for machine learning models.
* Feature Engineering: Transforming raw data into relevant features that can improve model performance.
* LSTM (Long Short-Term Memory):
* Recurrent Neural Networks (RNNs): Understanding the basics of RNNs, which are designed to work with sequence data.
* Cell State and Hidden State: The mathematical concepts behind LSTM's cell state and hidden state, which capture memory and information flow through time steps.
* Gates (Input, Forget, Output): How LSTM gates control the flow of information.
* Loss Functions and Optimization:
* Mean Squared Error (MSE): A common loss function used for regression tasks like stock price prediction.
* Adam Optimizer: An optimization algorithm used to minimize the loss function during training.
* Model Evaluation Metrics:
* Root Mean Squared Error (RMSE): A common metric for evaluating the accuracy of regression models.
* R-squared (R²): A metric that measures the proportion of the variance in the dependent variable that's predictable from the independent variables.
* Overfitting and Regularization:
* Overfitting: Understanding the concept of overfitting, where a model learns noise in the training data and fails to generalize well to unseen data.
* Dropout: A regularization technique used to reduce overfitting in neural networks.
* Time Series Forecasting:
* Time Steps and Look-Back Period: Defining the time steps used for prediction and the concept of a "look-back" period where historical data is considered.
* Visualization:
* Plotting Time Series Data: Using line plots to visualize historical stock price data.
* Loss Curves: Visualizing training and validation loss curves to monitor model performance.
* Financial Mathematics:
* Stock Returns: Understanding the concept of returns and how they relate to stock price changes.
* Risk and Volatility: Concepts related to market risk and volatility, often assessed using mathematical models like the GARCH model.
* Machine Learning Concepts:
* Supervised Learning: Understanding that stock price prediction is a supervised learning problem.
* Sequence-to-Sequence Models: Recognizing that LSTM models are a type of sequence-to-sequence model.