Autonomous Trading App Using Machine Learning.

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Abstract—Stock markets generate large volumes of data every day, and most trading applications present this data as charts and market information while leaving its interpretation to the user. This paper presents the design of an Autonomous Trading App that applies machine learning to historical stock market data in order to predict future price movements and to provide Buy, Sell, or Hold recommendations. Historical data are collected through the Angel One SmartAPI, preprocessed, and enriched with the technical indicators Moving Average (MA), Relative Strength Index (RSI), and Moving Average Convergence Divergence (MACD). A Long Short-Term Memory (LSTM) model, planned around TensorFlow, learns historical market patterns and predicts future price trends, and the prediction results are converted into trading recommendations. Stock prices, technical indicators, prediction graphs, portfolio details, and recommendations are presented on an interactive dashboard supported by user authentication and portfolio management. A review of five studies from 2023 shows that existing work concentrates on prediction performance and offers limited support for applications, recommendations, portfolio management, or user interaction, which motivates the proposed system. The system is intended for educational and research purposes rather than for real financial trading.

Key-Words—autonomous trading, machine learning, LSTM, stock price prediction, technical indicators, Buy/Sell/Hold recommendation, portfolio management, dashboard.

I. INTRODUCTION

A. Background and Motivation

The stock market generates a large amount of data every day, which makes it difficult for investors to analyze market trends and to decide on the right trading action. Most trading applications provide market data and charts, but they require users to interpret this information themselves. Deciding when to buy or sell a stock therefore remains a manual judgment, and the problem statement of this work notes that poor judgments of this kind often lead to poor investment decisions and financial losses.

Machine learning provides a means of learning patterns from historical market data. This paper describes the design of an Autonomous Trading App that uses machine learning to analyze historical stock market data, predict future price movements, and provide Buy, Sell, or Hold recommendations that assist users in making informed investment decisions. Prediction is performed by a Long Short-Term Memory (LSTM) model, and the input data are enriched with the technical indicators Moving Average (MA), Relative Strength Index (RSI), and Moving Average Convergence Divergence (MACD). The outputs are delivered through an interactive dashboard that also supports user authentication and portfolio management.

B. Objectives

The project pursues five objectives: (i) to analyze historical stock market data; (ii) to develop a machine learning model for stock price prediction; (iii) to provide Buy, Sell, or Hold recommendations; (iv) to display stock trends through an easy-to-use dashboard; and (v) to help users make informed trading decisions.

C. Contributions and Organization

This paper makes the following contributions. First, it consolidates the problem statement and the research gap from a review of five studies published in 2023. Second, it specifies an end-to-end methodology that extends from data acquisition to the presentation of recommendations. Third, it documents the technology stack and the hardware and software requirements. Fourth, it defines the scope, features, intended users, expected outcomes, and limitations of the system.

The remainder of the paper is organized as follows. Section II reviews related work. Section III states the problem and the research gap. Section IV describes the proposed system, and Section V presents the methodology. Section VI covers the technologies and methods. Section VII sets out the expected outcomes, Section VIII discusses them, and Section IX lists advantages and limitations. Section X concludes the paper.

II. RELATED WORK

Five studies published in 2023 were reviewed. All of them address stock price prediction from historical data with machine learning, but they differ in the models they use and in what they deliver to the end user. Table I summarizes the reported approach, the limitation noted for each study, and the contribution that the proposed system makes in response.

TABLE I
COMPARISON OF EXISTING METHODS AND CONTRIBUTION OF THE PROPOSED SYSTEM

Ref.	Study (2023)	Reported approach	Limitation noted	Contribution of the proposed system
[1]	Prediction of Stock Price Using LSTM, MA and EMA Models	Predicts stock prices using the LSTM model	Focuses on prediction accuracy; no user-friendly application or trading recommendations	Predicts stock prices and provides Buy, Sell, or Hold recommendations through a mobile application
[2]	Real-Time Future Stock Price Prediction Using Machine Learning Algorithms	Predicts future stock prices using historical data	No portfolio management or mobile interface for users	Provides a mobile app with stock prediction, recommendations, and portfolio management
[3]	Prediction of Stock Price Using Machine Learning Techniques	Uses historical data and technical indicators for prediction	No clear investment suggestions for users	Converts prediction results into easy-to-understand Buy, Sell, or Hold suggestions
[4]	Forecasting of Stock Prices Using Machine Learning Models	Compares different prediction models	Focuses only on forecasting performance; no interactive application	Integrates the prediction model into a user-friendly Flutter mobile application
[5]	Predicting Stock Price from Historical Data Using LSTM Technique	Uses LSTM for prediction	No real-time visualization or user interaction	Displays stock charts, prediction results, and recommendations in an interactive dashboard

A. LSTM-Based Prediction

The study in [1] predicts stock prices using the LSTM model. It concentrates on prediction accuracy and does not provide a user-friendly application or trading recommendations. The study in [5] likewise uses LSTM for prediction, but it does not offer real-time visualization or user interaction. Both studies therefore establish LSTM as a prediction technique while leaving the user-facing layer unaddressed.

B. Machine Learning Approaches Using Historical Data

The study in [2] predicts future stock prices using historical data with machine learning algorithms, but it does not include portfolio management or a mobile interface for users. The work in [3] uses historical data together with technical indicators for prediction, yet it does not give users clear investment suggestions. The study in [4] compares different prediction models and focuses only on forecasting performance; it does not provide an interactive application.

C. Synthesis

Taken together, the reviewed studies are prediction-centric. The limitations recorded for them concern the absence of a user-friendly or interactive application [1], [4], of trading recommendations or clear investment suggestions [1], [3], of portfolio management or a mobile interface [2], and of real-time visualization or user interaction [5]. These observations define the space in which the proposed system is positioned.

Table II arranges these limitations by capability. It records only what the source states for each study; a dash means that no statement was made, and it should not be read as evidence that the capability is present.

TABLE II
LIMITATIONS STATED FOR THE REVIEWED STUDIES

Ref.	Trading recomm.	User-friendly app	Portfolio / mobile	Real-time visual.	User interact.
[1]	×	×	–	–	–
[2]	–	–	×	–	–
[3]	×	–	–	–	–
[4]	–	×	–	–	×
[5]	–	–	–	×	×

×: limitation stated in the source;
–: not stated.

III. PROBLEM STATEMENT AND RESEARCH GAP

A. Problem Statement

Many investors find it difficult to analyze historical stock market data and to decide the right time to buy or sell stocks. Existing trading applications mainly provide charts and market information, but they do not offer intelligent predictions based on historical data. This often leads to poor investment decisions and financial losses.

B. Research Gap

The literature reviewed in Section II shows that prediction has received considerable attention, whereas the step from a prediction to an actionable, user-facing outcome has received less. Three gaps can be identified from the limitations in Table I. Fig. 1 relates each gap to the component of the proposed system that responds to it and to the corresponding expected outcome. The first is the conversion of prediction results into clear Buy, Sell, or Hold guidance. The second is the integration of the prediction model into a user-friendly application that includes portfolio management. The third is the presentation of prices, predictions, and recommendations through interactive visualization and user interaction. The proposed system is designed to address these three gaps within a single application, while retaining an LSTM-based predictor of the kind used in [1] and [5] and technical indicators of the kind used in [3].

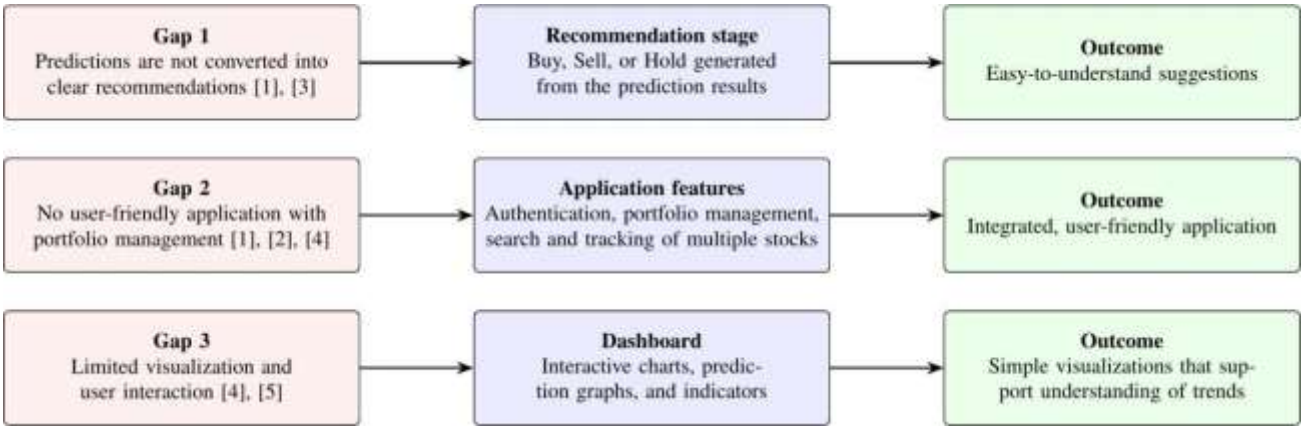


Fig. 1. Correspondence between the gaps identified in the literature, the components of the proposed system, and the expected outcomes.

IV. PROPOSED SYSTEM

A. Overview

The proposed Autonomous Trading App analyzes historical stock market data, predicts future price movements with a machine learning model, and provides Buy, Sell, or Hold recommendations. It differs from applications that only present charts in that the interpretation of the data is supported by a prediction and a recommendation. The recommendations assist users in making informed investment decisions; they are not intended to support real financial trading, as discussed in Section IX.

B. Scope

The scope of the project comprises six elements. (1) Historical stock market data are collected through the Angel One SmartAPI for market analysis and prediction. (2) The data are preprocessed, and features are engineered using the technical indicators MA, RSI, and MACD. (3) Stock prices are predicted with the LSTM model. (4) Buy, Sell, or Hold recommendations are generated from the prediction results. (5) An interactive dashboard displays stock prices, prediction graphs, portfolio details, and trading recommendations. (6) User authentication and portfolio management are provided. Fig. 2 shows these elements around the application.



Fig. 2. Functional scope of the proposed system, showing the six scope elements.

C. Features

The application includes user registration and login, historical stock data visualization, stock price prediction using LSTM, a Buy, Sell, or Hold recommendation system, interactive charts with a portfolio dashboard, and the ability to search and track multiple stocks.

D. Intended Users

Four groups of users are targeted: beginner investors, individual traders, students learning stock market analysis and machine learning, and researchers working on financial prediction systems. The first two groups use the application for market analysis and recommendations, whereas the latter two can use it to study the application of machine learning to financial market prediction.

V. METHODOLOGY AND SYSTEM ARCHITECTURE

A. Overall Workflow

The methodology follows a sequential pipeline from user interaction to the presentation of results, illustrated in Fig. 3. Each stage consumes the output of the preceding stage, so that the raw historical data are progressively transformed into a prediction, a recommendation, and finally a visual presentation for the user.

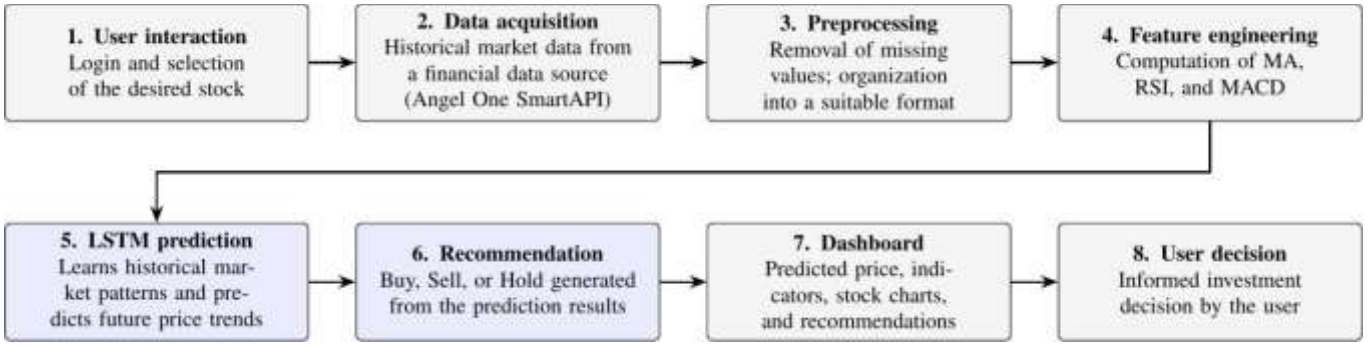


Fig. 3. Workflow of the proposed Autonomous Trading App, from user interaction to the presentation of recommendations.

Table III records the input and the output of each stage as stated in the methodology, which makes explicit how the stages depend on one another.

TABLE III
INPUT AND OUTPUT OF THE PIPELINE STAGES

Stage	Input	Processing	Output
User interaction	User credentials; choice of stock	Login and stock selection	Stock selected for analysis
Data acquisition	Selected stock	Collection from a reliable financial data source (Angel One SmartAPI)	Historical stock market data
Preprocessing	Historical stock market data	Removal of missing values; organization into a suitable format	Data in a format suitable for analysis
Feature engineering	Preprocessed historical data	Calculation of MA, RSI, and MACD	Processed data with technical indicators
LSTM prediction	Processed data	Learning of historical market patterns	Predicted future stock price trends
Recommendation	Prediction results	Generation of a recommendation	Buy, Sell, or Hold
Dashboard	Predicted price, indicators, charts, recommendation	Display on the application dashboard	Information for an informed investment decision

B. User Interaction and Data Acquisition

The user logs into the application and selects the desired stock for analysis. The application then collects historical stock market data from a reliable financial data source. The scope of the project specifies the Angel One SmartAPI for this purpose. Because the prediction is based entirely on historical data, the quality and organization of the collected data directly determine what the later stages can learn.

C. Preprocessing and Feature Engineering

The collected data are preprocessed by removing missing values and organizing them into a format suitable for analysis. Technical indicators are then calculated from the historical data. The indicators are the Moving Average (MA), the Relative Strength Index (RSI), and the Moving Average Convergence Divergence (MACD). Their inclusion follows the scope definition, which places feature engineering with technical indicators between data collection and prediction. The processed data, together with these indicators, form the input of the prediction model.

D. Prediction with the LSTM Model

The processed data are provided to the Long Short-Term Memory (LSTM) model, which learns historical market patterns and predicts future stock price trends. LSTM is also the model used for prediction in [1] and [5]. The proposed system differs from these studies in what happens to the prediction: rather than being reported as an end result, it is passed to the recommendation stage and to the dashboard.

E. Recommendation Generation

Based on the prediction results, the system generates a Buy, Sell, or Hold recommendation. This stage addresses the limitation noted in [1] and [3], where predictions are not turned into trading recommendations or clear investment suggestions. Presenting the outcome as one of three actions is intended to make the result easy to understand for users who may not be able to interpret raw predictions or indicator values.

F. Presentation on the Dashboard

Finally, the predicted stock price, the technical indicators, the stock charts, and the trading recommendations are displayed on the application dashboard, enabling users to make informed investment decisions. The dashboard also provides portfolio details and supports searching and tracking of multiple stocks, together with user registration and login. These functions respond to the lack of visualization, interaction, and portfolio management noted for the reviewed studies [2], [4], [5].

VI. TECHNOLOGIES AND METHODS

A. Technology Stack

The technology stack is grouped by function in Fig. 4. The frontend uses React.js, TypeScript, and Tailwind CSS. The backend uses Node.js, Java, and Python, together with a REST API. MongoDB Atlas and SQL are the listed database technologies. The machine learning components use Scikit-learn, NumPy, TensorFlow/Keras (for the LSTM), Pandas, and Matplotlib. Deployment is performed with Docker and Docker Compose.

Fig. 4. Technology stack of the proposed system, grouped by function.

Frontend	React.js · TypeScript · Tailwind CSS
Backend	Node.js · Java · Python · REST API
Database	MongoDB Atlas · SQL
Machine learning	Scikit-learn · NumPy · Tensor-Flow/Keras (LSTM) · Pandas · Matplotlib
Deployment	Docker · Docker Compose

B. Machine Learning Methods

The prediction model is an LSTM implemented with TensorFlow/Keras. Scikit-learn, NumPy, and Pandas support the machine learning and data handling tasks, and Matplotlib is listed for plotting. The technical indicators MA, RSI, and MACD serve as engineered features derived from the historical data, and the model output feeds the rule that produces the Buy, Sell, or Hold recommendation.

C. Development Environment and Hardware

Development is carried out in Visual Studio Code or Antigravity, with Git and GitHub for version control. The hardware and development requirements are listed in Table IV.

TABLE IV
HARDWARE AND DEVELOPMENT REQUIREMENTS

Category	**Requirement**
Processor	Intel Core i5 or AMD Ryzen 5
Memory	8 GB RAM (16 GB recommended)
Storage	256 GB SSD
Network	Internet connection
IDE	Visual Studio Code / Antigravity
Version control	Git, GitHub

VII. EXPECTED OUTCOMES AND EVALUATION

A. Status of Results

The project documentation from which this paper is prepared is a project synopsis. It defines the objectives, scope, methodology, and expected outcomes, but it does not report experimental results, datasets, or accuracy figures. This section therefore presents the outcomes that the proposed system is

expected to deliver rather than measured performance, and no quantitative claim is made about prediction accuracy.

B. Expected Outcomes

The proposed system is expected to deliver a user-friendly mobile application for stock market analysis; to analyze historical stock market data using machine learning techniques; to predict future stock price trends with improved accuracy; and to generate Buy, Sell, or Hold recommendations based on the prediction results. It is further expected to display stock charts, technical indicators, and prediction results in an interactive dashboard; to help users make informed trading decisions by providing AI-based insights; to improve users' understanding of stock market trends through simple visualizations and recommendations; and to demonstrate the practical application of machine learning in financial market prediction.

C. Relation of Objectives to the Methodology

Table V relates each objective of Section I to the stage of the methodology that realizes it and to the corresponding expected outcome.

TABLE V
OBJECTIVES, METHODOLOGY STAGES, AND EXPECTED OUTCOMES

Objective	**Stage**	**Expected outcome**
Analyze historical stock market data	Data acquisition, preprocessing, indicators	Analysis of historical data using machine learning techniques
Develop a prediction model	LSTM prediction	Prediction of future price trends
Provide Buy, Sell, or Hold recommendations	Recommendation generation	Recommendatins based on prediction results
Display trends on an easy-to-use dashboard	Dashboard presentation	Charts, indicators, and predictions in an interactive dashboard
Help users make informed decisions	All stages combined	AI-based insights and better understanding of market trends

VIII. DISCUSSION

The reviewed studies show that predicting stock prices from historical data with machine learning is well established, and that LSTM is a common choice for this task [1], [5]. The proposed system does not seek to replace these prediction techniques. Its contribution lies in placing a prediction model inside a complete application, so that a user proceeds from a stock selection to a recommendation and a set of visualizations without having to interpret raw data unaided. This directly addresses the problem statement, in which the difficulty of deciding when to buy or sell is attributed to applications that offer charts and information without intelligent predictions.

The combination of technical indicators with the LSTM model reflects the pairing of historical data and indicators found in [3] with the LSTM prediction used in [1] and [5]. The pipeline therefore keeps well-known ingredients but changes the point at which the result is delivered: the prediction becomes an intermediate product, and the recommendation and dashboard become the final products. For the intended users this matters in different ways. Beginner investors and individual traders receive a simple action-oriented output, whereas students and researchers can observe how a machine learning model is applied to financial market prediction.

Several caveats follow from the source material. The improved prediction accuracy listed among the expected outcomes is an objective and not a demonstrated result, and a quantitative assessment remains to be carried out once the system is implemented. Predictions rest on historical market data and may not always be accurate. Because inaccurate guidance in trading can lead to financial losses, the system is positioned as an educational and research tool, and its recommendations should be read as decision support and not as instructions for real trading.

IX. ADVANTAGES AND LIMITATIONS

A. Advantages

The system combines historical data analysis, LSTM-based prediction, Buy, Sell, or Hold recommendations, and an interactive dashboard in a single application. Users can search and track multiple stocks, view historical data and charts, and manage a portfolio after authentication. The results are presented through simple visualizations and recommendations, which is expected to improve users' understanding of stock market trends.

B. Limitations

Three limitations are stated for the system. First, it is intended for educational and research purposes and not for real financial trading. Second, external factors such as news events and global markets may affect accuracy. Third, predictions are based on historical market data and may not always be accurate. The second limitation indicates that the model relies on historical data and technical indicators only, as described in

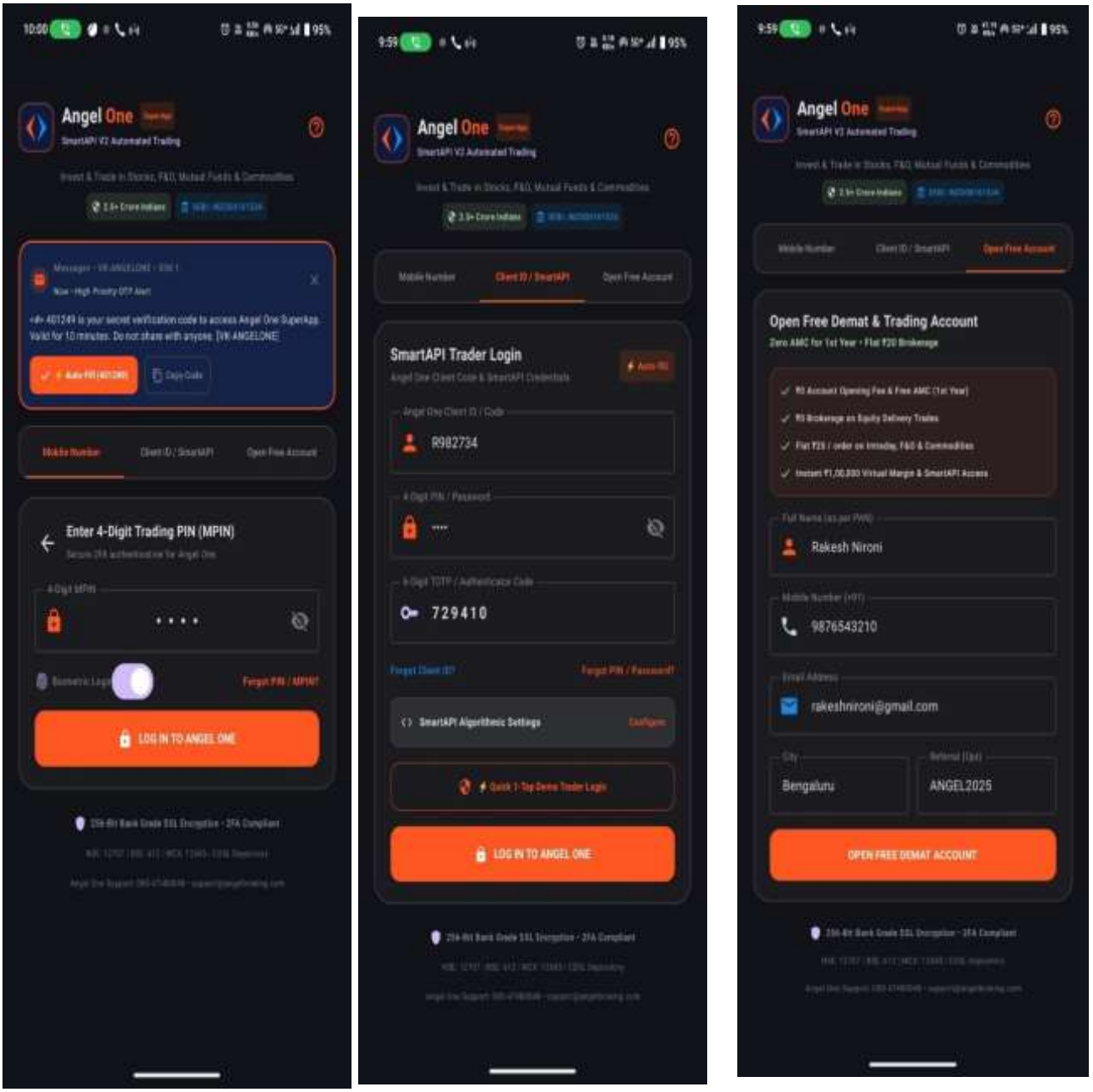
the methodology, and does not incorporate information on such external events.

X. CONCLUSION AND FUTURE WORK

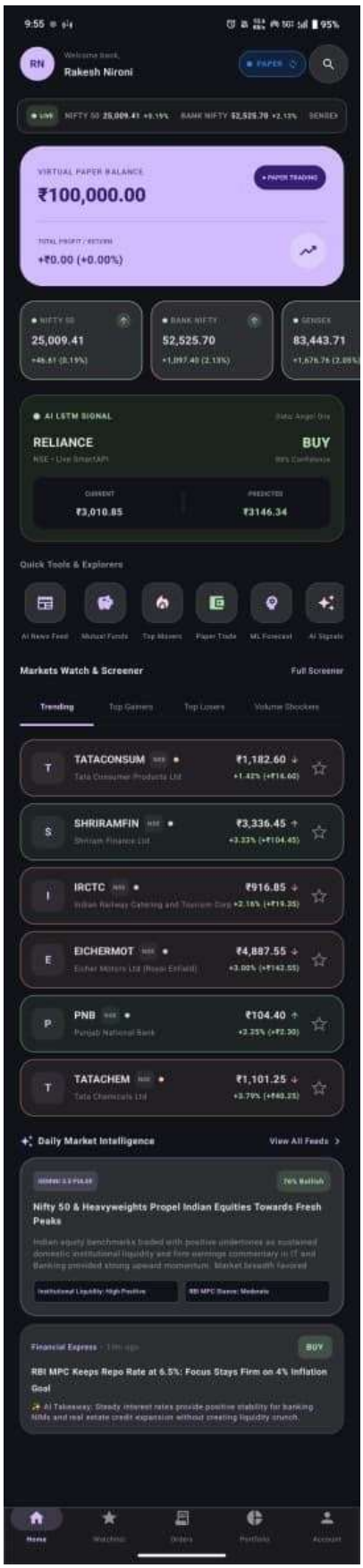
This paper presented the design of an Autonomous Trading App that applies machine learning to historical stock market data. The methodology collects data through the Angel One SmartAPI, preprocesses it, computes the technical indicators MA, RSI, and MACD, predicts future price trends with an LSTM model, generates Buy, Sell, or Hold recommendations, and displays the results on an interactive dashboard with user authentication and portfolio management. A review of five 2023 studies showed that existing work centers on prediction and provides limited support for recommendations, applications, portfolio management, and user interaction, and the proposed system is designed to close these gaps in one application for beginner investors, individual traders, students, and researchers.

Because the source material is a project synopsis, the paper reports expected outcomes and not measured results. The remaining work follows from this status and from the stated limitations: implementing the system as specified, evaluating the prediction and recommendation stages on the collected historical data, and examining how external factors such as news events and global markets, which the system does not currently account for, affect accuracy.

xi. SNAP-SHOTS



i. Login-page



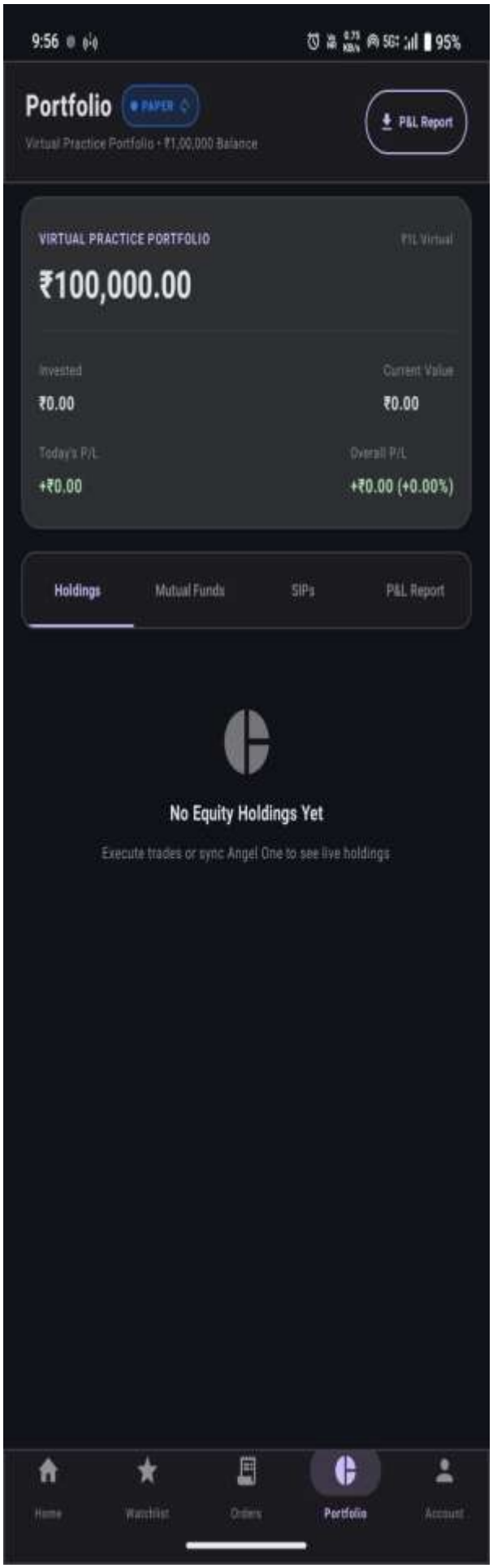
ii. Home Page



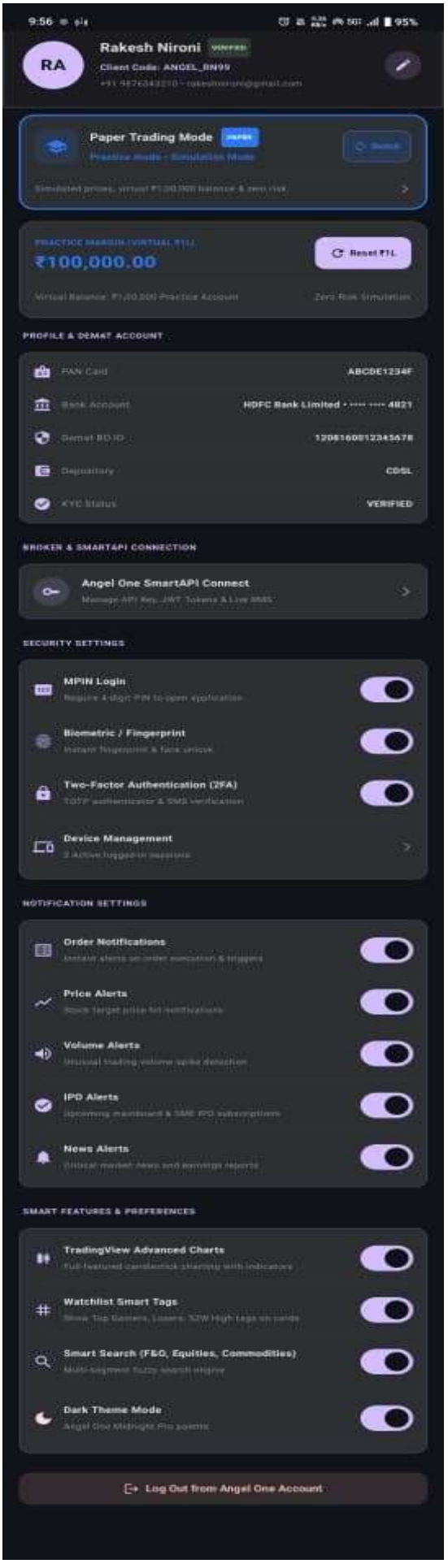
iii. Watchlist



iii. Orders



v. Portfolio



vi Profile

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