Smart Financial Literacy Tool

Prof. K. S. Shirke1, Sahiket Ghule2, Anushka Jadhav3, Abhishek Nangare4, Snehal Sasane5

[2,3,4,5] *Student, Department of Information Technology, SVPM's College of Engineering, Malegaon BK, Maharashtra, India.*

[1] *Assistant Professor, Department of Information Technology, SVPM'S College of Engineering Malegaon BK, Baramati, Maharashtra, India*

---***---

Abstract - The increasing complexity of financial systems has made financial literacy an essential skill, especially among students and young professionals. Many individuals lack proper knowledge of budgeting, saving, and investment planning, leading to poor financial decisions. To address this issue, we developed a Smart Financial Literacy Tool, an AI-based web application that helps users manage their finances efficiently. The system collects user data such as income, expenses, and savings, and uses machine learning algorithms like ARIMA and LSTM to predict gold and stock market trends. Based on these predictions and user financial profiles, the system provides personalized investment recommendations. Additionally, it includes an educational module to improve financial awareness and decision-making skills. The proposed system aims to bridge the gap between financial technology and financial education by combining prediction, recommendation, and learning in a single platform.

Key Words: Financial Literacy, Machine Learning, LSTM, ARIMA, Investment Prediction, AI, FinTech

1. INTRODUCTION

In today's rapidly evolving digital economy, financial literacy has become an essential life skill for individuals, especially students and young professionals. With the increasing use of digital payment systems, online investments, and financial applications, people are expected to make informed decisions regarding saving, budgeting, and investing. However, despite the availability of various financial platforms, many individuals lack the necessary knowledge to manage their finances effectively. This often leads to overspending, poor savings habits, and incorrect investment choices.

Existing financial applications mainly focus on transaction management, expense tracking, or investment execution. They provide limited guidance and lack personalized recommendations based on user behavior. Moreover, most platforms do not integrate predictive analytics or educational content, which are crucial for improving financial understanding and decision-making.

To address these challenges, this paper proposes a Smart Financial Literacy Tool, an AI-based system designed to assist users in managing their personal finances intelligently.

The system collects user financial data such as income, expenses, and savings, and applies machine learning algorithms like ARIMA and LSTM to predict gold and stock market trends. Based on these predictions and the user's financial profile, the system generates personalized investment recommendations. Additionally, it includes an educational module that helps users understand key financial concepts and improve their financial habits.

2. Problem Statement

Development of an intelligent financial literacy system that enables users to manage income, track expenses, and make smart investment decisions using AI-based analysis. The system will predict gold and stock market trends using machine learning algorithms and provide personalized investment recommendations along with financial education to improve user awareness and decision-making.

3. Literature Survey

In recent years, the use of Artificial Intelligence (AI) and Machine Learning (ML) in financial applications has increased significantly. Many systems have been developed for expense tracking, investment analysis, and financial recommendation. Studies show that machine learning algorithms such as Linear

Regression, Decision Trees, and Random Forest can be used to analyze financial data and provide useful insights. Some platforms also use time-series models like ARIMA and LSTM to predict stock and gold price trends based on historical data. These models help in understanding behavior and improving investment decisions. However, most existing systems focus only on prediction or transaction management and lack integration with financial education and personalized recommendations.

4. MOTIVATION

The rapid growth of digital financial systems has increased the need for proper financial knowledge among individuals. However, many users still lack awareness about budgeting, saving, and investment planning. Existing applications mainly focus on transactions and do not provide complete guidance or learning support. The proposed Smart Financial Literacy Tool is motivated by the need to create an intelligent system that combines financial prediction, personalized recommendations, and educational content

A. Improving Financial Awareness

Many students and young professionals do not have a clear understanding of basic financial concepts such as budgeting, saving, interest rates, and investment planning. This lack of knowledge often leads to poor financial decisions and financial instability. The proposed system helps users learn these concepts through simple explanations, tips, and interactive content, thereby improving their overall financial awareness and confidence.

B. Supporting Better Investment Decisions

Most individuals invest money without analyzing market trends or understanding risks. This can lead to losses or ineffective financial planning. By using machine learning algorithms such as ARIMA and LSTM, the system predicts gold and stock price trends based on historical data. These predictions help users make informed and data-driven investment decisions instead of relying on guesswork.

C. Personalized Financial Guidance

Financial planning differs from person to person based on income, expenses, goals, and risk tolerance. Existing systems provide general suggestions that may not suit every user. The proposed system analyzes user-specific data and generates personalized recommendations, such as how much to save, where to invest, and how to manage expenses effectively.

D. Bridging the Gap between Technology Education

Most financial applications focus only on managing money but do not educate users about financial concepts. As a result, users depend on the system without understanding the reasoning behind decisions. This tool combines both financial education and AI-based analysis, helping users not only follow recommendations but also understand them.

E. Ensuring Simplicity and Accessibility

Financial tools are often complex and difficult for beginners to use. The proposed system is designed with a simple and user-friendly interface that allows users to easily enter their data, view results, and understand recommendations. It is accessible through web and mobile platforms, making it convenient for all types of users.

F. Promoting Financial Discipline

Many individuals face difficulties in managing their daily expenses and maintaining consistent saving habits due to lack of proper planning and financial awareness. Uncontrolled spending and absence of budgeting often lead

to financial instability and stress. The proposed system helps users build financial discipline by analyzing their spending patterns and providing regular insights and alerts. It encourages users to follow good financial practices such as budgeting, tracking expenses, setting savings goals, and planning for future needs. By promoting these habits, the system helps users achieve long-term financial stability and make more responsible financial decisions.

5. System Architecture

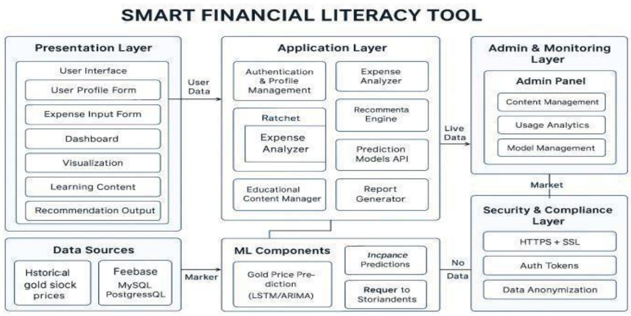

Fig 1: System Architecture

1. User Registration & Authentication: Users securely register and log in to access personalized financial services and manage their data.

2. Add Financial Data: Users input details such as

income, expenses, savings, and financial goals for analysis.

3. Financial Analysis: The system analyzes user data to understand spending patterns and financial behavior.

4. Recommendation to User: The system provides personalized investment suggestions and saving strategies based on prediction results.

5. Access to Other Health Systems: The system provides educational materials to improve financial knowledge and awareness.

6. Proposed Algorithms

Algorithm 1: LSTM (Long Short-Term Memory)

LSTM (Long Short-Term Memory) is an advanced type of Recurrent Neural Network (RNN) designed to process sequential and time-dependent data. Unlike traditional models, LSTM is capable of learning long-term dependencies by maintaining memory through special units called gates. In the context of this project, LSTM is used to analyze historical financial data such as gold and stock prices to identify hidden patterns and trends overtime.

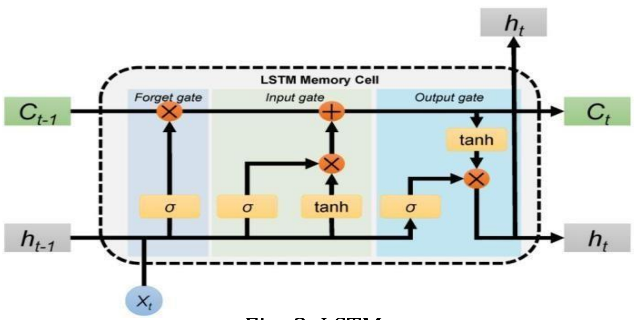

Fig -2: LSTM

Explanation of ARIMA:

1. Input: Historical financial data such as gold prices and stock market values is collected over time

2. Dataset and preprocessing: The data is cleaned and transformed into a stationary form using differencing techniques to remove trends and seasonality.

Model Training: Once parameters are selected, the ARIMA model is trained on the processed dataset. The model learns the relationship between past observations

Explanation of LSTM:

1. Input: The system collects historical financial data such as gold prices and stock market values over a specific time period.

2. Dataset and preprocessing: The collected data is cleaned to remove missing or inconsistent values, normalized for uniform scaling, and converted into sequential format suitable for time-series modeling.

3. Model building: An LSTM neural network is designed with multiple hidden layers and memory cells to capture long-term dependencies in the data.

4. Training Phase: The model is trained using historical datasets where it learns patterns, trends, and variations in financial data.

5. Prediction Phase: The trained model processes new input data and predicts future values of gold and stock prices.

6. Output and Recommendation: Based on predicted trends, the system provides intelligent investment suggestions and financial insights to the user.

Algorithm 2: ARIMA (Auto-Regressive Integrated Moving Average)

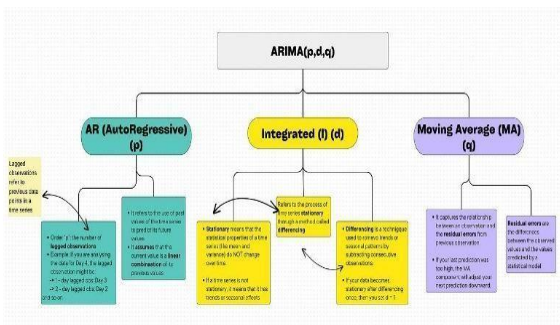

Fig 3. ARIMA

Prediction process: The trained model uses learned patterns to forecast future financial values. It generates predictions by combining past

Result and recommendation: The predicted results are analyzed to identify trends (increasing, decreasing, or stable). Based on these trends, the system provides investment suggestions such as whether to invest, hold, or avoid certain assets.

Algorithm 3: Decision Tree

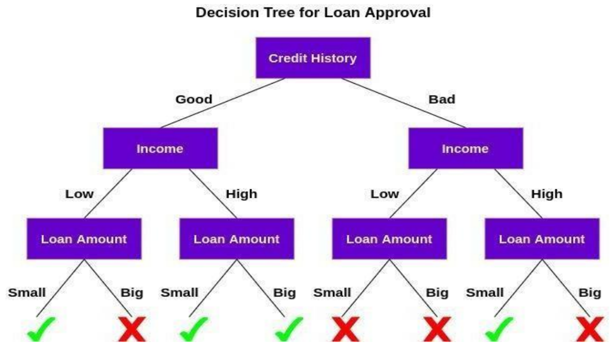

Fig 4. Decision Tree

Explanation of Decision Tree:

1. Input: The system collects user financial data such as income, expenses, savings, and risk preference

2. Dataset and preprocessing: The collected data is cleaned, organized, and converted into a structured format suitable for model training.

3. Model building: A decision tree is built by selecting the best features for splitting the data based on criteria like Information Gain or Gini Index.

4. Training Phase: The model is trained using historical data, where it learns patterns and decision rules for classifying financial behavior

5. Prediction Phase: The trained model processes new user input and classifies the user into categories such as low- risk, medium-risk, or high-risk investor.

6. Result and recommendation: Based on classification, the system provides personalized investment suggestions such as safe investments, balanced portfolios, or high-return options.

Algorithm 4: Linear Regression

1. Input: The system collects user financial data such as income, expenses, savings, and investment preferences. These variables act as input features for the model.

2. Dataset and preprocessing: The collected data is cleaned by removing inconsistencies and handling missing values. Numerical scaling or normalization may be applied to ensure all features are within a comparable range.

3. Model building: A Linear Regression model is created by defining the relationship between input variables (independent variables) and the target variable (dependent variable such as savings or future expenses).

4. Training Phase: The model is trained using historical user data. During training, the algorithm calculates coefficients (β values) by minimizing the error using methods like Least Squares, ensuring the best fit line is obtained.

5. Prediction Phase: Once trained, the model predicts future financial values such as expected savings or expenses based on new user input data

6. Result and recommendation: The predicted results are analyzed to provide financial insights such as budgeting suggestions, saving strategies, and expense control recommendations to help users improve their financial planning.

I. Accuracy

• LSTM Algorithm: LSTM provides high accuracy for time- series financial data as it captures long-term dependencies and complex patterns in stock and gold price trends.

• ARIMA Algorithm: ARIMA offers good accuracy for short- term forecasting and performs well on stable and linear time-series data, but may struggle with highly non-linear patterns

• Decision Tree Algorithm Decision Tree provides good accuracy for classification tasks and can handle complex decision-making scenarios, but may suffer from overfitting if not properly optimized.

• Linear Regression Algorithm: Linear Regression provides moderate accuracy as it assumes a linear relationship between variables, making it suitable for basic financial predictions like income and expense analysis.

II. Computational complexity

• LSTM Algorithm: LSTM has high computational complexity due to its deep neural network structure, multiple hidden layers, and memory cells. It requires significant computational resources and training time.

• ARIMA Algorithm: ARIMA has moderate computational complexity. It involves operations like differencing, parameter estimation, and iterative model fitting. While it is less complex than deep learning models.

• Decision Tree Algorithm: Decision Tree has moderate computational complexity. The complexity increases with the depth of the tree and number of features, as the algorithm evaluates multiple splits to find the best decision rules.

• Linear Regression Algorithm: Linear Regression has low computational complexity as it uses simple mathematical calculations to find the best-fit line. It is fast to train and efficient even with large datasets, making it suitable for real-time financial analysis

III. Real-Time Performance

• LSTM Algorithm: LSTM provides moderate real-time performance. While prediction is relatively fast after training, the training process itself is time-consuming due to complex neural network computations and sequential data processing.

• ARIMA Algorithm: ARIMA offers good real-time performance for short-term forecasting. Once the model is trained, it can generate predictions quickly, making it suitable for real-time financial trend analysis.

• Decision Tree Algorithm: Decision Tree provides fast real- time performance during prediction. Once the model is built, it quickly classifies input data using simple decision rules, making it efficient for real-time recommendation systems.

• Linear Regression Algorithm: Linear Regression provides excellent real-time performance because of its simple mathematical structure. It can generate predictions almost instantly, making it highly suitable for real-time financial analysis and quick decision-making.

IV. Generalization to New Data

• LSTM Algorithm LSTM has strong generalization ability for time-series financial data as it learns long-term dependencies and patterns. When trained on sufficient and diverse datasets, it can adapt well to new and unseen market trends

• ARIMA Algorithm: ARIMA provides moderate generalization performance. It works well when future data follows similar patterns as historical data, but its performance may decrease when there are sudden changes or non-linear fluctuations in financial markets.

• Decision Tree Algorithm: Decision Tree can generalize well if properly optimized using techniques like pruning. However, it may overfit training data and perform poorly on new data if the tree becomes too complex without regularization.

• Linear Regression Algorithm: Linear Regression has limited generalization capability for complex financial data, as it assumes a linear relationship between variables. It performs well on simple and consistent data

In conclusion, the proposed Smart Financial Literacy Tool provides an intelligent and user-friendly platform for managing personal finances. It uses machine learning algorithms such as LSTM, ARIMA, Linear Regression, and Decision Tree to analyze financial data and predict market trends. The system also offers personalized investment recommendations and financial education to improve user awareness. Overall, it helps users make better financial decisions and promotes long-term financial stability.

7. METHODOLOGY

The proposed Smart Financial Literacy Tool is designed to analyze user financial data and provide predictions and recommendations using machine learning techniques. The system follows a structured process as described below:

I. Data collection and Input

User health data is collected through the NaariCare interface:
• Users enter details such as age, menstrual cycle history, symptoms (acne, weight gain, irregular periods), and hormonal information
• Data is stored securely for further processing and analysis.

II. Data Preprocessing

The collected financial data undergoes preprocessing to ensure quality and consistency.
• Data Cleaning: Handling missing or inconsistent values in income, expenses, and market data
• Encoding: Converting categorical data into numerical format for processing
• Normalization: Scaling values to a uniform range for better model performance

III. Feature Selection and Dataset Preparation

Relevant financial features are selected to improve prediction.

• Important attributes like income level, expense patterns, savings ratio, and market trends

- Dataset is divided into training and testing sets
- Helps in reducing noise and improving model efficiency

IV. Model Training using LSTM and ARIMA

Machine learning models are trained using prepared datasets:

- LSTM: Used for time-series prediction of stock and gold prices
- ARIMA: Used for statistical forecasting of market trends
- Models learn patterns between user data and financial outcomes

V. Prediction & Classification

The trained models are used to predict financial trends and user

- New user input is passed into the models
- LSTM and ARIMA predict future market prices
- Regression and Decision Tree analyze financial patterns

class.

- Output is generated as predicted finamcial trends

VI. Result Generation and Recommendation

Based on prediction results, the system provides actionable insights:

- Displays predicted stock and gold price trends
- Suggests personalized investment options.
- Provides saving strategies and expense management tips

VII. System Integration and Continuous Learning

The complete model is integrated into the NaariCare platform:

- Enables real-time prediction and user interaction
- New user data can be added to improve model accuracy over time
- Ensures scalability and continuous system enhancement

8. Results

a. Stock Price Prediction

Model	Type	Accuracy	Real time capability	Comments
LSTM	Recurrent Neural Network	92	Medium	Captures long-term trends well
ARIMA	Statistical Model	85	High	Good for short-term forecasting
Linear Regression	Supervised Learning	80	High	Simple but less accurate

Table1: Stock Price Prediction

b. Gold Price Prediction

Model	Type	Accuracy	Real time capability	Comments
LSTM	Recurrent Neural Network	91	Medium	Handles time-series patterns well
ARIMA	Statistica2l Model	84	High	Stable and efficient
Linear Regression	Supervised Learning	78	High	Works for basic trend analysis

Table 2 : Gold Price Prediction

c. Financial Recommendation

Model	**Type**	**Accuracy**	**Real time capability**	**Comments**
LSTM	Deep Learning Model	88	Medium	Supports trend-based suggestions
ARIMA	Statistical Model	83	High	Useful for short-term insights

Table 3: Financial Recommendation

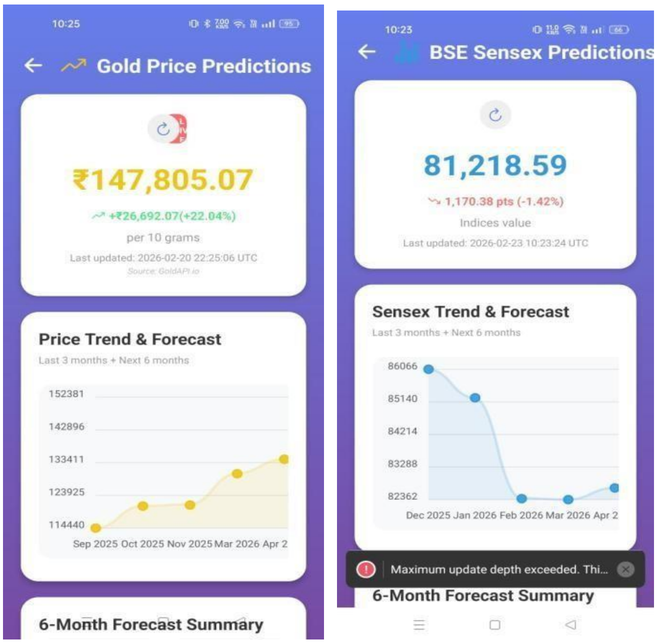

Fig.5 Gold & BSE Sensex Prediction Dashboards

3. CONCLUSION

The proposed Smart Financial Literacy Tool provides an effective and intelligent solution for managing personal finances using machine learning techniques. By integrating models such as LSTM, ARIMA, Linear Regression, and Decision Tree, the system is able to analyze financial data, predict market trends, and generate personalized investment recommendations. The platform also enhances financial awareness through educational content and visualization tools. Overall, the system helps users make informed financial decisions, improves financial discipline, and supports long-term financial planning.

REFERENCES

[1] A. Lusardi and O. S. Mitchell, “Financial literacy and planning: Implications for retirement wellbeing,” National Bureau of Economic Research (NBER), Working Paper No. 17078, 2011.

[2] R. Thaler and S. Benartzi, “Save More Tomorrow™: Using behavioral economics to increase employee saving,” Journal of Political Economy, vol. 112, no. S1,

[3] pp. S164–S187, 2004

[4] A. Jain, P. Chandra, and A. K. Jain, “Personal finance management using data analytics,” International Journal of Computer Applications, vol. 179, no. 7, pp. 15–20, 2018.

[5] T. Beck, A. Demirgüç-Kunt, and P. Honohan, “Access to financial services: Measurement, impact, and policies,” The World Bank Research Observer, vol. 24, no. 1, pp. 119–145, 2009.