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Wise Wallet: A Companion for Saving Smarter and Investing Better

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ABSTRACT—

As financial independence and literacy become the most sought after commodities, people are increasingly searching for unorthodox solutions in order to help people take financial control. This report describes a fully realized financial assistance package that uniquely integrates two powerful experience features - spartan expense tracking and intelligent stock market predictions - into a single user-centric interface. At the same time, it uses a ML model which is a part of ensemble learning called decision tree to provide future stock price predictions that utilizes actual measured data and surpasses market trends. The model is extensively preprocessed and evaluated with significant performance metrics to prospective identified secure output-reliability. Both features are tailored into a robust, consumer-friendly platform that permits individuals to monitor their personal account finances and undertake informed investment plans. Thus, this research paper delves into the world of finance and machine learning and reduces the gap between them so that technology seeps in these respective fields. The chatbot is built on Natural Language Processing (NLP) technology for the users to naturally interact through text, facilitating automatic tagging and categorization of costs by contextual understanding. The users can provide queries or statements regarding their finances, and the chatbot will process and classify the information efficiently without needing manual entry or tagging. Complementing this is the stock forecasting module, which is driven by the Random Forest algorithm due to its capacity for dealing with massive datasets, filtering noise, and providing high-accuracy predictions. It forecasts stock trends based on historical data in the form of closing prices, trading volume, and short-term trends. The efficacy of the system is ensured through evaluation measures such as precision, recall, and F1-score for classification-based tasks and Mean Squared Error (MSE) and R^2 score for regression-based stock forecasting. By merging the convenience of chatbot-based expense management with the smartness of machine learning-based stock prediction, the system provides an integrated, easy-to-use platform. It not only assists users in handling their present-day financial transactions but also assists them in making wise investment choices for the future.

Keywords—Stock prediction, Machine learning, Artificial Intelligence, Random Forest, Natural Language Processing, Datasets, Regression algorithms, Generative AI

1. Introduction

The task of managing personal finance is usually tedious and involves many time consuming tasks like monitoring day to day expenses, monitor monthly budget and also make wise decisions when it comes to investments. This intimidating experience was earlier managed by using manual techniques like spreadsheets or financial planners. With a rapid and evolving changes in the information technology, more solutions for various issues are introduced. This paper implements a system that combines two essential features in personal finance management: a stock prediction model and an expense tracking chatbot. These help simplify financial decision-making by providing insight and organization using one system. The expense management and tracking capability is based on Natural Language Processing (NLP). This feature allows the users to communicate with the chatbot that is capable of understanding the context behind messages and classifying financial data automatically. The chatbot learns from interpreted financial data and is able to recognize various keywords and transaction types, and then save them to the respective category without explicitly needing to classify the input. This makes it easier for the customer to manage and maintain expenditures. Along with this, the system also contains a stock prediction module with Random Forest algorithm which uses previously available stock data to predict potential future prices. The system considers various features like closing prices, volumes, and short-term trends for its prediction. The choosing of Random Forest is due to its capability of handling large amounts of data, noise handling in the data, and for providing good prediction accuracy through the accumulation of many decision trees.

The system components are developed through careful data preprocessing and training using task-specific data. The performance measure of the model is done using features like precision, recall, and F1-score, and the stock predictor is measured through metrics such as MSE and R^2 score. These measures help to ensure that every part works consistently for various provided inputs.

Many users these days prefer tools that can perform multiple tasks without having to switch between various platforms. Hence, this system includes both an expense chatbot and a stock prediction model in the same system making it more convenient for users who are looking to manage their budget and also to explore investment opportunities.

The kind of system is useful for various groups of the society like students, working professionals, or anyone trying to develop better financial habits. It not only helps users keep a close watch on their finances but also helps them to understand the basics of stocks and investments. With the integration of expense tracking driven by NLP and stock prediction by using machine learning, the developed system helps users with everyday spending and long-term investment plans. It provides an easy -to-use, yet smart solution for financial troubles and helps simplify tasks and boost productivity.

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II. LITERATURE SURVEY

Fuli Feng et al. (2018) proposed a stock movement prediction model using LSTM that is enhanced with adversarial training.[1] Small perturbations were introduced during the training process, which helped the model become more robust to market noise and also improved its generalization ability. The model was evaluated on real-world stock datasets, and it outperformed standard models by 3.11% relative improvements in accuracy.

A hybrid model comprising of an Attention-based CNN-LSTM with XGBoost was developed by **Zhuangwei Shi et al. (2022)** for predicting stock prices. Preprocessing and fine-tuning were done using the ARIMA model and the XGBoost model respectively.[2] The results showed that the hybrid model was more effective and had a comparatively higher prediction accuracy when compared to the standard models. Important feature-level patterns captured in the hybrid model lead to better accuracy.

Varisha Ashraf et al. (2018) developed an AI-powered chatbot called Fynbot for personal expense management. The system combines Natural Language Processing (NLP) and Artificial Intelligence (AI) to help users in managing their finances through user interactions and conversational interfaces.[8] Various technologies such as the Stanford NLP library, IBM Watson for AI capabilities, and Hidden Markov Models for sequence prediction were implemented. The chatbot is implemented on the Android platform to provide the users with a convenient tool to track expenses and to maintain finance budget.

Rohit Tamrakar and Niraj Wani (2021) presented a detailed review on the design and development of chatbots that use both rule-based and AI-based architectures. The review explored the use of various features like Natural Language Processing (NLP), machine learning, and speech recognition to amplify user interactions with the chatbot.[9] It also reviews the technique, terminology, and different platforms used to design and develop the chatbot. The utility of the chatbot tool for Computer-Aided Design (CAD) applications is proposed from this review.

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Yang Li and Yi Pan (2020) proposed a deep learning approach to predict future stock movement. It consisted of a two-level ensemble deep-learning model that contains an LSTM and GRU network that was combined together along with a fully connected layer that uses both previous price data and financial news to predict stock trends.[3]To make appropriate predictions, numerical data was merged with sentiment analysis to extract relevant market sentiment. The model achieved a 57.55% reduction in mean.

III, Methodology:

Proposed Solution:

To address the need of a financial aid, The proposed solution involves stock prediction model which is divided into multiple steps listed as follows:

- Data acquisition
- Model Selection
- Training process
- Gradio implementation and testing

The expense management chatbot is integrated to provide users with financial guidance like schemes running in the government.

Together the models are integrated in Gradio where they work efficiently hand in hand.

The stock prediction model is first explained in detail.

1) Data Acquisition:

Data acquisition is a very important step in prediction aspects. It predicts the closing price accurately when a stock ticker (for example GOOG for Google) is given as input. For the stock prediction module, the data is collected using the yfinance API. A set of almost 50 stocks were tracked and listed. This makes sure that the model has the capability to predict stock closing price over a large range of data stocks.

The chatbot was designed to give tips and guidance on managing finance, so to support these intents a collect of curated responses were created using the financial section of the official government portals, articles and blogs, manually defined templates. The token matching approach of nlp processing is implemented for each finance topic. These tokens are based on all of the frequently asked questions and patterns are seen in user queries.

Feature extraction:

For the stock prediction module, relevant financial indicators were applied from the dataset retrieved from yfinance. The features used for training include close and open price which are the price at which the market closes and opens respectively. The features high and low depicts the highest and lowest price of the day. Volume is the total number of shares traded. In addition to this MA10 ,MA20 ,EMA10 ,STD20 ,Return, Volume Change, RSI, MACD, Close lag and target are the additional features extracted for data processing. These features are selected for increasing the performance of the model and maintain consistent values for prediction.

Since the chatbot is implemented with rule bsed NLP token matching, features are derived by tokenizing the user input and matching them with predefined phrases and keywords.

Figure 3.1 depicts the features extracted for the stock prediction model

```
✨ Features extracted:
• ('Close', 'AAPL')
• ('High', 'AAPL')
• ('Low', 'AAPL')
• ('Open', 'AAPL')
• ('Volume', 'AAPL')
• ('MA10', '')
• ('MA20', '')
• ('EMA10', '')
• ('STD20', '')
• ('Return', '')
• ('Volume_Change', '')
• ('RSI', '')
• ('MACD', '')
• ('Close_Lag1', '')
• ('Close_Lag2', '')
• ('Target', '')
```

Fig 3.1 Features extracted for the stock prediction model

2) Model Selection:

Since the dataset consisted of numerical values, regression algorithms must be applied. After a careful consideration of various algorithms, the Random Forest Regressor was selected as the core model for stock price prediction. This is because random forest handles non linearity and offers faster training and predictions making it suitable for real time Gradio applications. The expense management chatbot uses simple NLP technique called token matching which tokenizes input prompts and matches them to the predefined actions.

3) Training of the model:

The Random forest was trained using the historical data of 5 years using the API.Before training the data underwent feature scaling and now the dataset is divided into two subsets which is used for training and testing. The model is trained with n_estimators value to be 100. The training was completed therefore making sure of the model's ability for deployment using the Gradio interface.

The chatbot which follows token matching as a more structural training process which starts by designing all the keyword patterns and the logic for conversation. The chatbot was trained with saving and budgeting, investment advice, Schemes announced by the government and loan related inquiries. The response is crafted with rich examples and real world examples.

Fig 3.2 The training process done on GOOGL ticker.

The figure 3.8 showcases the training done for one of the ticker GOOG (short for google) and the confidence score of 96.89% is given for the prediction.

4) Gradio implementation and testing:

To provide a seamless and an interactive user experience, the expense management chatbot and the stock prediction model were integrated together and were deployed together using Gradio which is an open-source python library which enables a fast interface for models. There is no need to code in a different platform other than Google Colab to deploy the models as the platform supports in-live interface in the notebook.

Chatbot deployment was implemented within the Gradio Interface block. The code function takes the user input as text, tokenizes the input into a set of tokens and then matched the pattern with the trained data and returns the predefined response. A textbox for user input , a text display screen to show the response of the chatbot is displayed on the screen. Since the chatbot is created as a text in-voice out model, the output given by the chatbot is converted to audio file which is shown on the output screen

Both the models are deployed in the same Gradio interface. The interface is also designed to give an approximated graph of all the closing prices for a period of 5 years.

Flowchart:

The representation of the system methodology in terms of a flowchart is given below.

The flowchart depicts the system workflow of a dual-use intelligent financial assistant system aimed at aiding users in both expense control and stock market prediction. System interaction starts with user input, in which the user requests a question or information—this might be a question for budgeting, tracking expenses, or investment desires.

This input is then processed by the chatbot, which uses Natural Language Processing (NLP) to determine the intent of the user. Depending on the processed input, the chatbot responds accordingly—either by providing advice pertaining to personal finance, saving behaviour, or expense management, or by asking follow-up questions to narrow down the context.

After this, the system determines if the user shows interest in stocks. This is a branching logic to either go ahead with stock services or follow with normal financial advice. If the user is not interested in stock forecasts, the chatbot ends after providing appropriate financial advice. In case the user shows interest in stocks, the flow moves into the stock forecast path. In this, the user is asked to enter the name of the stock he is interested in. After inputting the name of the stock, the system executes the stock prediction model based on the Random Forest algorithm. This machine learning model takes historical stock information—previous closing prices, volumes, and recent trend in the market—to forecast the probable future performance of the stock.

After processing, the projected future trend or stock price is shown to the user, guiding them to a well-informed investment choice. The prediction result is shown in a comprehensible form, maybe with graphical trends or plain labels such as "increase", "decrease", or "stable", depending on the user interface. The whole pipeline makes sure users receive contextual, goal-directed help—whether handling everyday spending in uncomplicated interactions or making fact-based decisions on stock investments. The system subsequently cleans up elegantly, ready to receive the next input or session.

Fig 3.3 represents the graphical representation of the system methodology.

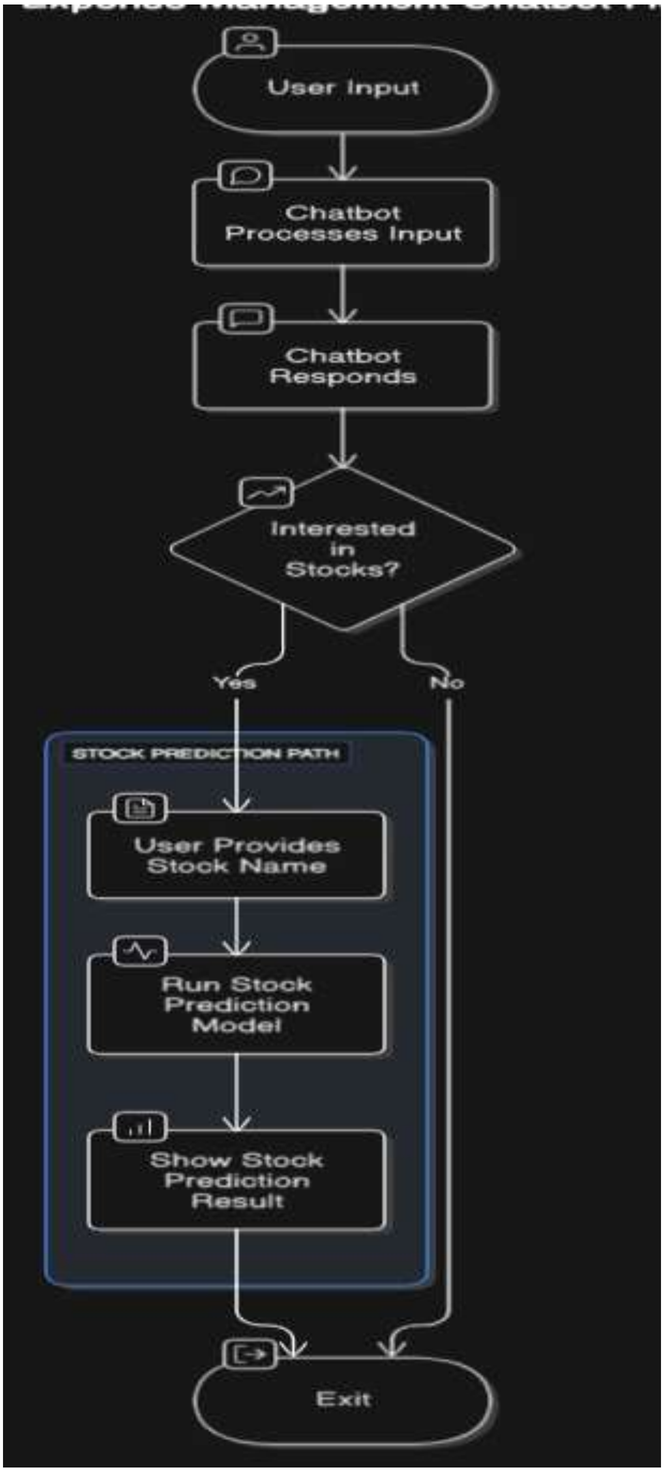

Figure 3.3 System methodology

IV. Results and discussion:

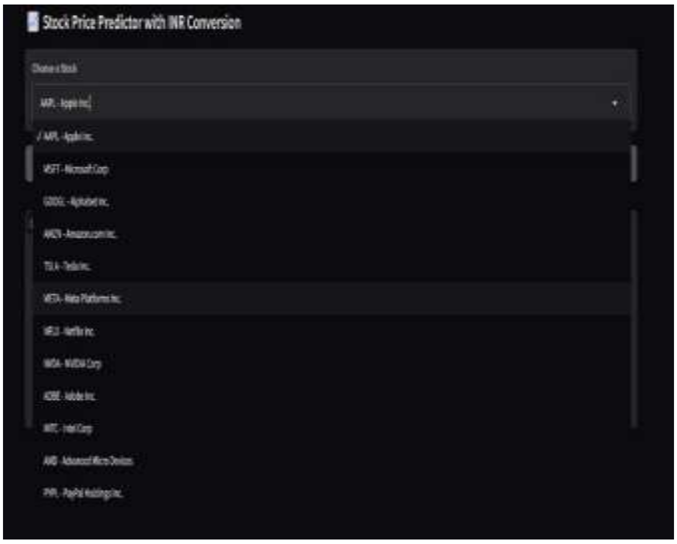

Fig 4.1 Stock Selection Dropdown for Prediction

Fig 4.1 shows a dropdown option with a selected list of popular tech and finance stocks. Each list item contains the ticker for the stock followed by the full company name (e.g. AAPL - Apple Inc.) so that users can identify the company they want to analyse. This list contains major companies such as Apple, Microsoft, Amazon, and Tesla, providing users with established well known stocks to review and predict. After the stock is selected, the application will then fetch relevant historical data that can be used for prediction. This intuitive UI component makes the prediction tool more user-friendly and interactive for users who may not remember stock symbols.

Fig 4.2 Stock Forecast Dashboard

Figure 4.2 illustrates the forecast price which is used to close for the following day, with values converted to INR. In the case of META (Meta Platforms Inc.), the model presents both the actual closing price for today and the anticipated closing price for the next day. Additionally, a mini graph depicts the closing prices over the past five years, offering a concise overview of the stock's trend over time to enhance investment and decision making. This front-end, built using Gradio, enables intuitive interaction with the model, combining real-time stock predictions with currency conversion and a performance overview, all supported by an easy-to-read graph.

Prediction Summary:

	Ticker	Today_Close	Predicted_Tomorrow	Actual_Tomorrow	Confidence (%)
0	AAPL	194.27	205.28	196.98	92.65
1	MSFT	371.61	399.14	367.78	96.30
2	GOOGL	153.33	154.52	151.16	96.89
3	AMZN	174.33	173.19	172.61	96.32
4	IBM	238.57	231.46	238.81	91.65
5	TSLA	241.55	246.86	241.37	89.46
6	NVDA	104.49	103.96	101.49	96.13
7	META	502.31	503.26	501.48	98.34
8	NFLX	961.63	977.34	973.03	95.03
9	INTC	19.23	19.34	18.93	99.65
10	ORCL	129.76	130.44	128.62	96.02
11	AMD	88.29	113.32	87.50	97.16
12	BABA	106.75	106.00	108.87	96.38
13	ADBE	344.19	415.07	348.80	94.03
14	CRM	249.84	248.50	247.26	92.95
15	CSCO	55.76	56.40	55.76	99.31
16	PYPL	60.24	60.99	61.00	98.57
17	QCOM	135.74	154.13	136.66	97.18
18	SHOP	83.96	83.62	83.65	96.93
19	UBER	73.06	73.17	75.24	98.65

Fig 4.3 Stock Prediction Summary Table

In Figure 4.3 we can see a comparative analysis of some of the most known stocks for technology companies, showing their predicted and actual prices for the day and indicating their performance over the Previous trading day. The table has Today Close price, Predicted Tomorrow stock price, and Actual Tomorrow prices for each stock. There is also a Confidence column that shows how much trust the model has in the validity of its prediction. Stocks like INTC and CSCO show confidence levels that are above 99%. This data is all in one table which is very useful for investors to check how accurate the predictions are for different companies and how the model performs with different companies, all through an interface powered by Gradio.

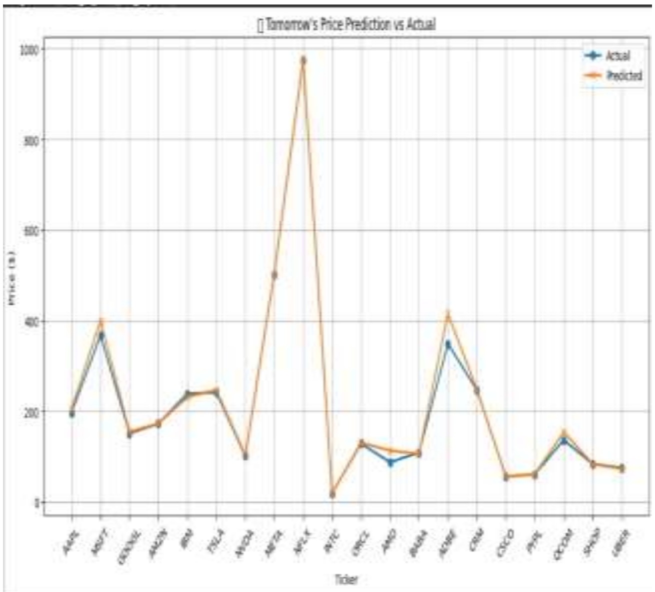

Fig 4.4 Comparison of Predicted vs Actual Stock Prices

Fig. 4.4 shows the next-day actual and predicted closing prices of 20 tech stocks. Each stock is represented on the x-axis by its ticker symbol, and the y-axis denotes the price of the stock in USD. Each ticker has two lines: the predicted price is portrayed by an orange line, while the actual price is a blue line. The closeness of the predicted and actual price across most tickers provides evidence that the predicted prices were close, as seen with stocks such as NFLX, INTC, and CSCO which had nearly identical predicted and actual values. Bigger deviations are noticed in some examples, like ADBE and BABA, which are hinting at stocks where prediction somewhat over-estimated or under-estimated. Nevertheless, the picture overall effectively verifies the accuracy of the model through presenting an understandable picture of the prediction accuracy over all the selected stocks.

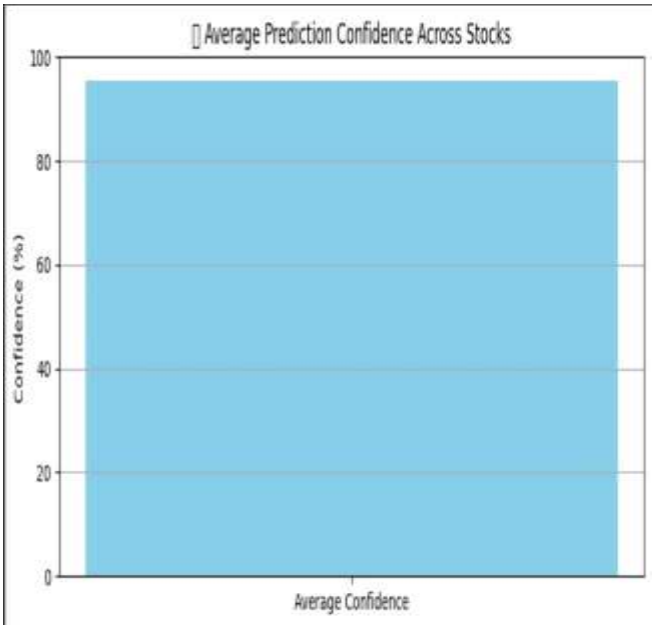

Fig 4.5 Overall Confidence Level of Stock Price Predictions

The chart depicted in Fig. 4.5 illustrates the overall confidence level of the stock price prediction model. The x-axis shows a combined confidence metric from all predicted stocks, while the y-axis shows a confidence level measured from 0% - 100%. The chart measures confidence with a single blue bar that nearly reaches the top of the chart. The average confidence in the predictions was approximately 95%. Overall, this chart demonstrates the strength and consistency of the stock prediction unit and model. This chart confirms the reliability and robustness of the stock forecasting system. It ensures that users have confidence in the fact that the model is making choices with high confidence, and this is vital when the forecasts are to be used in making financial choices or investment strategy development.

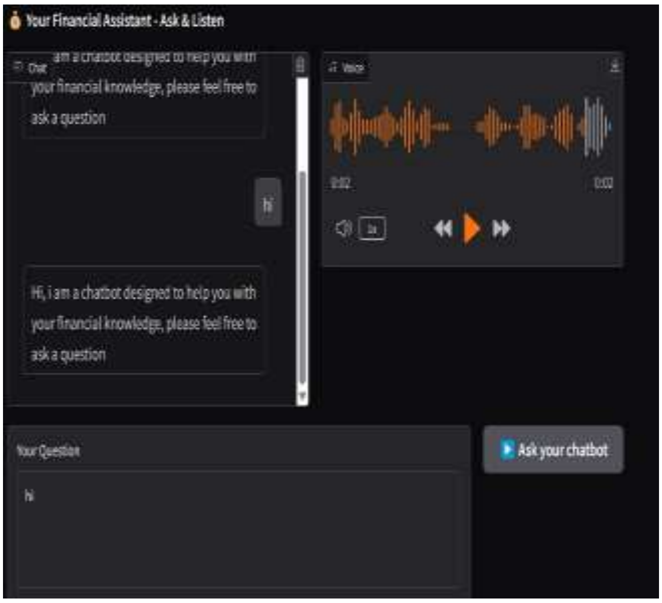

Fig 4.6 Financial Chatbot Interface Overview along with Voice assistant

In Fig 4.6 shows an example of the user interface for a voice-enabled financial chatbot that supports users' financial knowledge through both text and voice interactions is shown. A audio file is displayed on the screen to the right of the interface which is a translation from text to audio enabling the model to work as a voice assistant. Overall this chatbot operates as a digital financial assistant, making more accessible to users by enabling them to do their financial tasks.

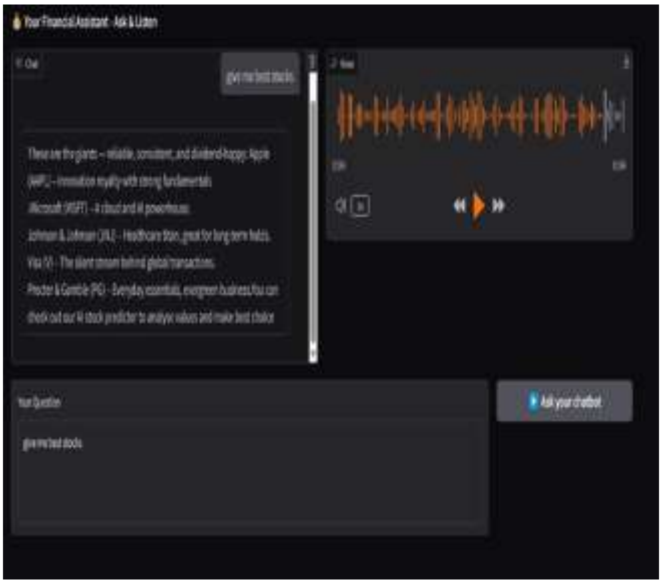

Fig 4.7 Image recognition interface

Fig 4.7 represents the interface where users can give a prompt with respect to finance and the chatbot returns the user a proper response within its data. For instance, if the user types in a query "give me best stocks" then the chatbot returns performing stocks. The chatbot's reply can also be obtained in audio format as an option as well. Finally, a message will be displayed asking users to check out the stock prediction model if interested. At the bottom, the latest query of the user "give me tips on debt management" is still in the input area, with an easily identifiable "Ask your chatbot" button close by, encouraging additional queries.

In general, this voice-based financial chatbot acts as an amiable digital coach, assisting consumers in navigating through complicated financial choices with a non-threatening and friendly interface. Personalized answers engage users to seize control of their finances by presenting actionable advice in a straightforward, interactive manner.

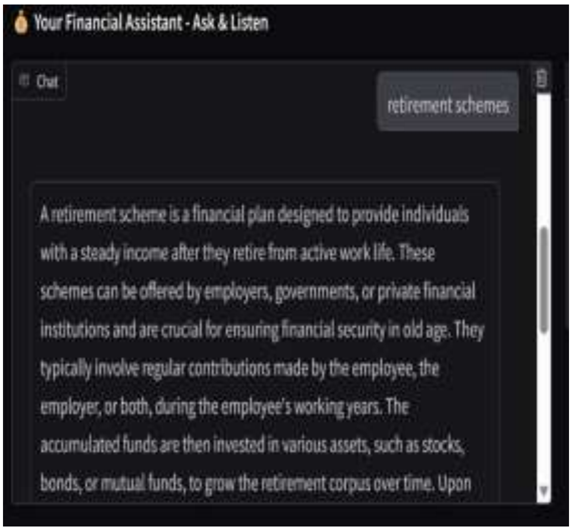

Fig 4.8 Smart Financial Assistant Interface

Fig. 4.8 shows user has typed in “retirement schemes,” as a prompt to find out about financial planning for life after retirement and the chatbot provides a complete and helpful response, this chatbot serves as a financial educator in the digital space, responding to everyday financial queries with helpful and informative responses. This intelligent assistant is an important tool for users to help them understand complex financial matters into simple, basic language.

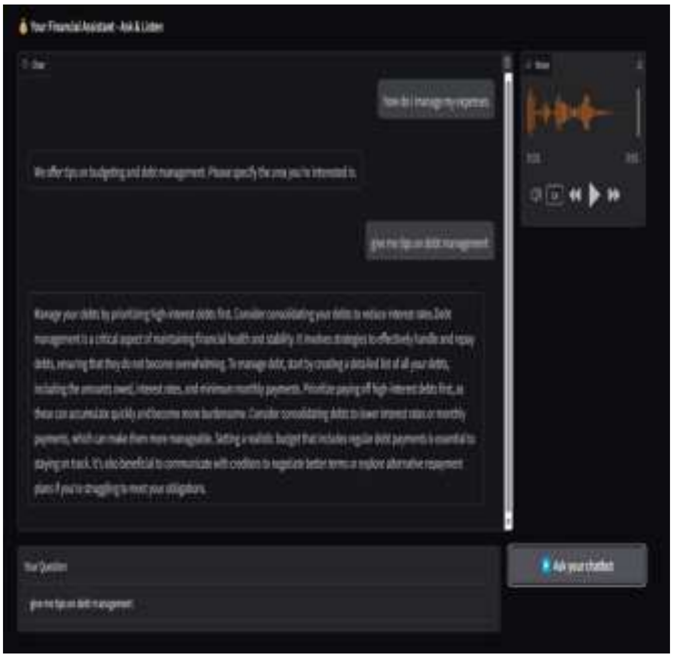

Fig 4.9 Smart Debt Management Guidance

Fig 4.9 shows this smart financial assistant chatbot is intended to instruct users on how to manage their finances efficiently through smart budgeting, expense monitoring, savings tips, and investment strategies. Here a user queries how to handle expenses and asks for debt management tips. The chatbot offers concise and useful guidance like paying off high-interest debts first, rolling over loans to lower interest rates, and creating a realistic budget with frequent debt repayments. It urges users to keep a list of their debts in detail and be regular with payments to ensure no financial pressure. The chatbot also suggests open communication with lenders to negotiate improved terms or alternative payment solutions. A feature is also added where users can hear the chatbot's suggestions in voice play-back, suitable for users who desire auditory advice. The tool seeks to enable users with the information and assistance they require to manage their financial well-being and make smart money choices.

V.CONCLUSION AND FUTURE ENHANCEMENTS:

This project exhibits the successful fusion of Natural Language Processing (NLP) and machine learning in order to implement a complete personal finance assistant. By merging stock prediction and expense tracking into a single system, the system facilitates users to deal with their money more effectively as well as to make smart investments. The NLP-driven chatbot enables users to communicate with the system naturally, without technical expertise, and assists them in automatically tracking and categorizing their expenses. Meanwhile, the Random Forest-based stock forecasting feature uses past trends and current market conditions to provide accurate future forecasts. The dual-functionality of the system renders it not only user-friendly but very practical for daily use.

What makes this model stand out from others is its seamless integration of two essential financial tools in one place. Unlike other systems that focus only on expense management or just on investment suggestions, our project offers both features while ensuring ease of access through a smart chatbot interface. Utilization of the Random Forest algorithm gives a strong advantage with its capability in dealing with noisy, intricate data and generating more precise results with ensemble learning. The expense classification is avoided manually by the chatbot as it learns from user inputs and arranges data automatically, thereby saving effort and time. The scope of the project in the future involves incorporating live stock market data to enable predictions to be more dynamic in terms of responding to current market trends.

It can also extend to include other areas of finance like cryptocurrency, mutual funds, and even provide customized savings suggestions. Features such as voice command, multilingual interfaces, and profiling of users for customized financial suggestions can also render the system more dynamic and accessible. Overall, the project is an effective and adaptable solution for personal finance management, aimed at making tasks easier and enabling users to make better financial decisions based on data-driven insights.

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