ISSN: 2959-6386 (Online), Vol. 2, Issue 3

Journal of Knowledge Learning and Science Technology

journal homepage: https://jklst.org/index.php/home

Personalized Financial Recommendations: Real-Time AI-ML Analytics in Wealth Management

Munivel Devan[1], Ravish Tillu[2], Lavanya Shanmugam[3]

[1]Fidelity Investments, USA
[2]RBC Capital Markets, USA
[3]Tata Consultancy Services, USA

Abstract

Recent studies reveal a concerning lack of financial literacy among millennials, highlighting the need for comprehensive education in managing personal finances. Financial literacy is not only crucial for employability but also for navigating life successfully. Many individuals, including those in the corporate sector, struggle with financial planning and decision-making. In response, awareness in wealth management has emerged as a vital solution. Wealth management extends beyond mere investment advice; it encompasses various financial services tailored to individuals' needs, addressing all aspects of their financial lives. By leveraging artificial intelligence and machine learning principles, individuals can access comprehensive information on various investment options and develop personalized financial plans. This approach empowers individuals and their families to effectively manage both current and future financial needs.

Keywords: Artificial Intelligence, Investment Advisory, Machine Learning, Wealth Management System

ArticleInformation:
Article history: *Received:*01/12/2023 *Accepted:*10/12/2023 *Online:*16/12/2023 *Published*: 16/12/2023
DOI: https://doi.org/10.60087/jklst.vol2.n3.p559

Correspondence Author: Munivel Devan

Introduction

Wealth management is a comprehensive investment advisory service that integrates various financial offerings to meet clients' needs. Through this process, advisors analyze and anticipate client requirements, tailoring bespoke strategies using suitable financial products and services. Clients typically remunerate wealth management advisors or managers for such financial guidance. Advisors assess clients' financial standings and recommend suitable investment amounts and vehicles based on their circumstances. Wealth management extends beyond mere investment advice, encompassing all aspects of an individual's financial well-being.

Users of wealth management systems can access consolidated information on diverse investment options, eliminating the need to gather data from multiple sources. They can manually generate financial plans or leverage artificial intelligence and machine learning techniques to assist in managing their own and their family's present and future financial needs. Contrary to common belief, wealth management is not solely reserved for affluent individuals. With the emergence of the millennial workforce, there is a growing demand for accessible guidance and insight into the realm of finance before individuals can confidently navigate it. Our website aims to provide a user-friendly platform that demystifies the financial landscape and streamlines access to information.

Through our website, individuals can explore various investment opportunities and understand their intricacies. They can make informed financial decisions with the aid of features such as return calculators, financial plan generators, stock market predictors, and stock market simulators.

Objectives of the Study

In the contemporary landscape, technology plays a pivotal role, and the primary aim of the wealth management system is to streamline the management of individuals' finances. It endeavors to establish a platform where users can make well-informed and optimal financial decisions. The system relies on user-provided input parameters crucial for accurately computing and presenting the best-suited investment options.

Employing various principles of machine learning and artificial intelligence, our objective is to precisely categorize individuals into high-risk, medium-risk, and low-risk categories. Based on their risk category, users will gain access to diverse financial plans and calculators to gauge the potential returns on their investments. Ultimately, our goal is to ensure a seamless user experience while fostering expertise in financial literacy.

Organization of the Paper

• Related Work: This section delves into existing systems akin to the proposed one, delineating crucial features that require attention.

• Proposed Methodology: Here, we outline the design of the proposed system and its modular division to enhance comprehension.

• Results and Discussion: This segment encompasses the installation, testing, and utilization of software pertinent to system development. Additionally, it discusses various observations made during implementation.

• Conclusion and Future Scope of the System: The paper culminates with a conclusion highlighting key findings and potential avenues for future system enhancements.

Literature Review

Numerous existing works delve into various aspects of wealth management, providing valuable insights for the development of our system. These works have been reviewed to identify essential features to be incorporated into our system and to explore potential enhancements for user benefit. Several notable works include:

A. Stock Market Analysis and Prediction Co-Authored by Eric Alexander, Emily Kawaler

This paper highlights the multifaceted influences on stock market data, ranging from economic factors to geopolitical events. It explores diverse prediction approaches such as neural networks, fuzzy reasoning, and support vector machines (SVM) with SMO. Notably, the paper assesses the efficacy of linear regression, random forests, and SVM in predicting future prices and trends across various stocks.

B. Study on Machine Learning Techniques in Financial Markets Co-Authored by Prakhar Vats, Krishna Samdani

This study delves into the core pillars of the financial world, including portfolios, securities, and stock market forecasting, emphasizing the critical role of accurate prediction in financial decision-making. It implements various machine learning algorithms to address financial market challenges, evaluating parameters like accuracy, efficiency, speed, and usability to inform algorithm selection.

C. Finbingo

Finbingo emerges as a recent entrant in the financial decision-making landscape, offering users a platform to define financial goals and develop corresponding plans. Through Finbingo, users gain insights into various investment options tailored to their objectives, underscoring the importance of user connectivity and accessibility in financial assistance platforms.

These works collectively contribute to our understanding of wealth management systems, guiding the development of our system to meet user needs effectively.

Methodology

The proposed system is structured into four distinct modules, each tailored to accommodate varying risk levels of investment options and user preferences:

A. Customer Module:

This initial module serves as the entry point for users, where they input personal details, earnings, expenses, and savings. Leveraging artificial intelligence principles, the system generates tailored financial plans based on these inputs, providing personalized recommendations.

B. Low-risk and Medium-risk Module:

The second module caters to low and medium-risk investments, offering users secure options such as fixed deposits and PPFs for low-risk investments, and mutual funds for medium-risk investments. Additionally, this module features calculators to estimate returns based on users' selected investments.

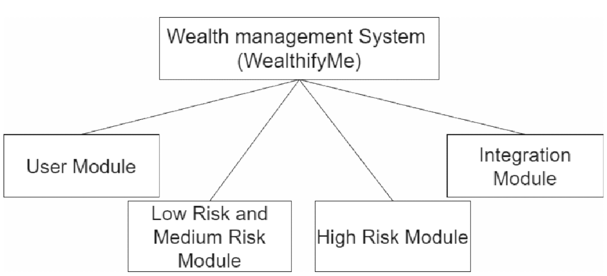
C. High-risk Module:

Designed for users seeking higher returns, this module focuses on high-risk investments like the stock market. Leveraging machine learning principles, the system identifies stocks with potential for increased profitability, providing users with predictive insights. Users can also manually search for specific stocks and access corresponding predictions.

D. Integration Module:

In this final module, all preceding modules are integrated to construct the website. Front-end implementation and system development are carried out here, ensuring seamless user experience and functionality across the platform.

This modular approach allows for comprehensive coverage of investment options across varying risk levels, empowering users to make informed financial decisions aligned with their risk preferences and investment objectives.

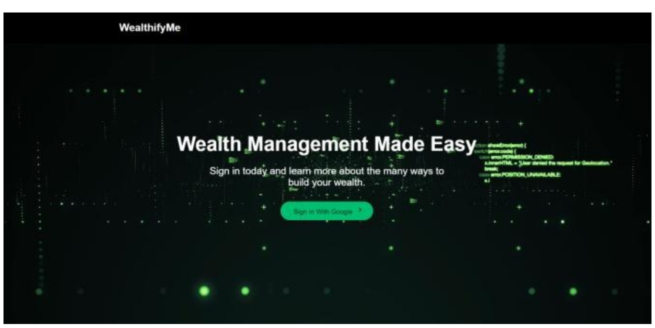


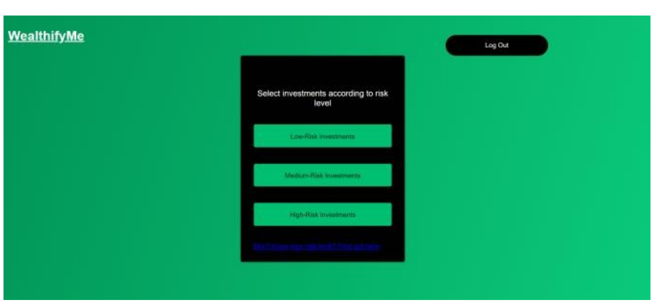
Implementation

A. Website Development

The website is implemented using React, a JavaScript library renowned for its efficient creation of user interfaces. React enables the development of single-page applications, offering a declarative, powerful, and versatile approach to building reusable UI components. As an open-source, component-based front-end library, React simplifies the creation of reusable UI components and facilitates the development of large-scale web applications capable of dynamic data manipulation without page reloading. With a focus on speed, scalability, and usability, React primarily operates within the application's user interface layer.

In the website's architecture, React corresponds to the view component of the MVC (Model-View-Controller) template. Upon accessing the website, users are presented with the homepage. Non-registered users are directed to the sign-up section, where they can create an account. New users are required to fill out a form providing various information necessary for categorizing them based on their risk level.





B. Customer Segmentation Based on Risk Level

Customer segmentation involves categorizing customers into distinct subgroups based on their unique needs. Traditionally, this process was manual, lacking precision and efficiency. However, with the advent of artificial intelligence (AI) and machine learning principles, segmentation can now be optimized to leverage resources and data effectively, aligning with business objectives. AI-driven segmentation can range from simple categorizations like gender and age to more complex risk level preferences.

The Customer Segmentation Process is as follows:

- Pre-processing:

The data undergoes cleaning and transformation to ensure its suitability for analysis. Establishing a "gold standard" training dataset is essential for future use.

- Modeling:

Algorithms are applied to identify variables crucial for segmentation. These variables are then prioritized and incorporated into the "gold standard" training dataset, allowing the model to learn shared characteristics among segments.

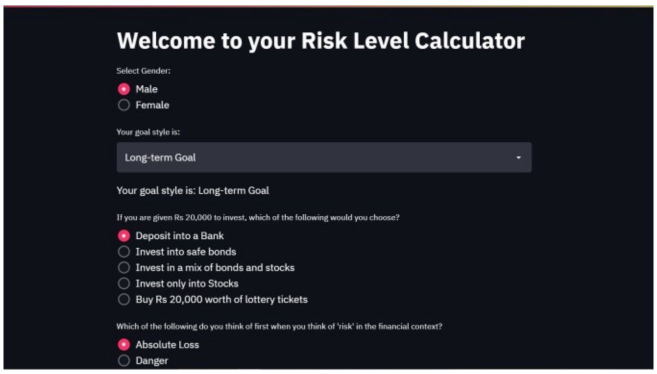
- Evaluation:

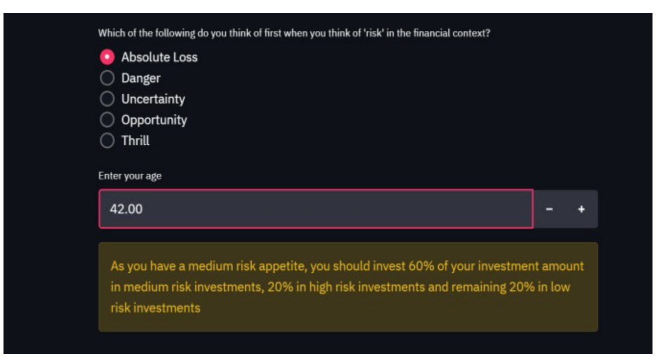
Evaluation involves using matrices to identify previously misclassified contacts and assess the model's accuracy. Statistical coefficients may address class imbalances in datasets with uneven segment representation.

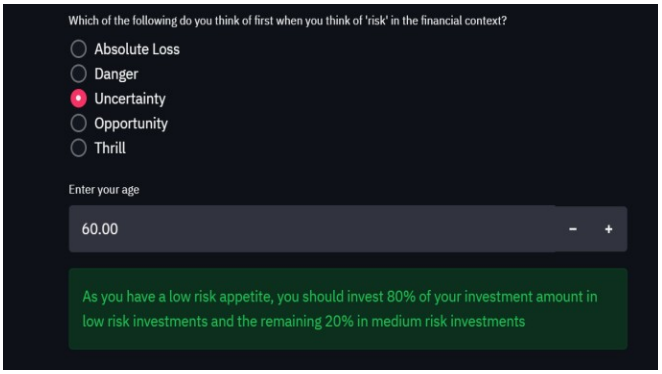
- Output:

With the data transformed, customers are segmented based on the "gold standard" training dataset.

Users can determine their risk appetite by completing a form containing information such as age, gender, and personality-based questions. This form enables users to understand their risk profile effectively.







C. Low-risk and Medium-risk Investments (Return Calculator)

Our Returns Calculator empowers users to estimate the returns on their desired investments accurately. Just like any calculator, it comprises different sections where users input various parameters relevant to their investment, allowing for precise determination of investment returns.

D. High-risk Investments (Stock Price Prediction)

Prediction problems have long been challenging in the realm of data science, encompassing a wide array of issues ranging from sales forecasts to market data pattern recognition. When it comes to stock price prediction, today's stock price is influenced by several factors:

- Trends: The prevailing trend in the stock's performance over previous days, whether upward or downward.
- Previous Price: The stock's price on the preceding day, as many traders reference the previous day's price before making investment decisions.
- Influencing Factors: Various factors that can impact today's stock price, such as changes in company policies, declines in profits, or unexpected shifts in senior leadership.

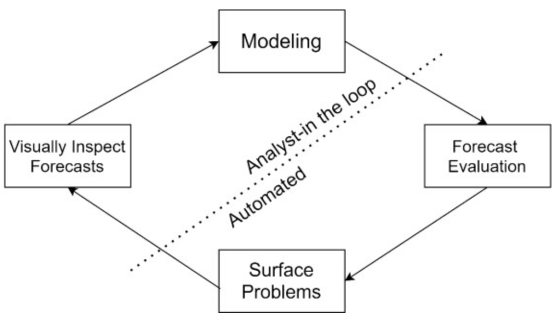
Prophet, an additive regression model, is employed for stock price prediction. It fits non-linear patterns incorporating annual, weekly, and daily seasonality, as well as the influence of holidays:

- Change Point Detection: Prophet identifies pattern changes by selecting change points from the data.

- Yearly Seasonality: Utilizes a Fourier series-based yearly seasonal variable.

- Weekly Seasonality: Incorporates dummy variables to create a weekly seasonal component.

- Custom Holiday Impact: Allows users to specify important holidays affecting stock prices.



Results and Discussions

A. Prophecy Library:

Forecasting plays a crucial role in anticipating future trends and developments based on historical data inputs. It is widely recognized as a significant data science challenge within organizations today, as it aids in goal-setting, policy-making, and strategic planning. Prophet, a method designed to address these challenges, offers a practical approach to scalable forecasting. Its goal is to provide accessible methods that can be customized to automate common features of time series forecasting in business contexts.

Prophet empowers analysts from diverse backgrounds to generate more accurate predictions than they could manually. The Prophet toolkit includes user-friendly parameters that are easily adjustable. Even individuals with no prior experience in forecasting models can utilize Prophet to generate precise forecasts for various business scenarios. These components are combined in the following equation:

\(y(t) = g(t) + s(t) + h(t) + \varepsilon_t \)

Where:

- \(g(t) \): Piecewise linear or logistic growth curve for modeling non-periodic changes in time series.

- \(s(t) \): Periodic changes (e.g., weekly/yearly seasonality).

- \(h(t) \): Effects of holidays with irregular schedules.

- \(\varepsilon_t \): Error term accounting for any unusual changes not accommodated by the model.

Prophet adopts a decomposable time series model, consisting of five main components:

- Automatic detection of trend changes by selecting changepoints from the data.

- Modeling of yearly seasonal component using Fourier series.

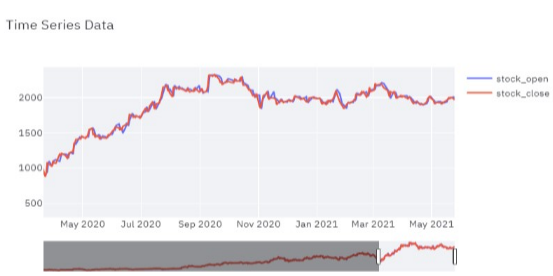
- Incorporation of a weekly seasonal component using dummy variables.

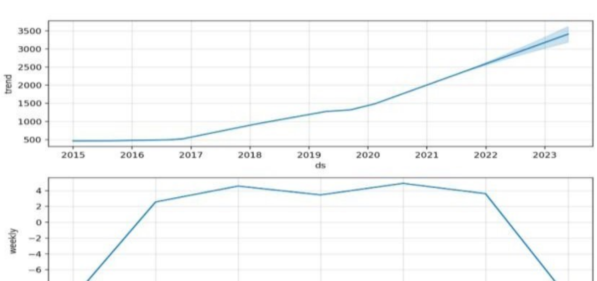
- Inclusion of a user-provided list of important holidays.

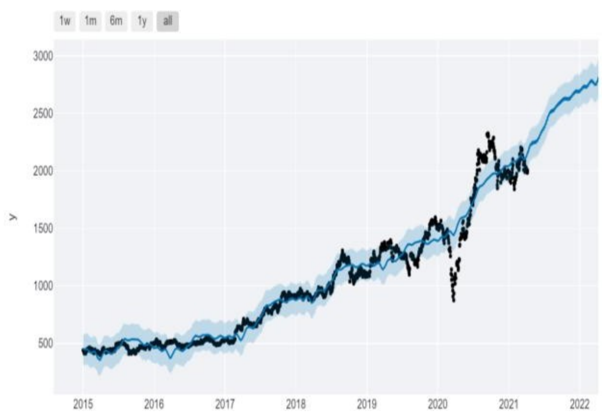
We applied this model to Reliance stock data to assess prediction accuracy and error percentage. The model achieved a root mean square error of 1.2, indicating its effectiveness in generating accurate predictions.

Raw data

	Date	Open	High	Low	Close
1569	2021-05-19T00:00:00+0…	1982	2,016.6000	1,972.1000	1,996.3500
1570	2021-05-20T00:00:00+0…	1,996.3500	2,010.8000	1,981.1000	1,985.3000
1571	2021-05-21T00:00:00+0…	1,995.7000	2009	1980	2,000.9000
1572	2021-05-24T00:00:00+0…	2,007.4000	2,009.5000	1,981.6000	1,985.5500
1573	2021-05-25T00:00:00+0…	1,990.0500	1997	1,960.1000	1,964.5000







B. LSTM:

We also utilized Long Short-Term Memory (LSTM) neural networks to forecast the closing price of Apple and Netflix stocks using data from Yahoo Finance. This model can be applied to predict the stock prices of any company by simply replacing the company name in the code.

Prediction problems have been prevalent for a long time and are considered some of the most challenging tasks in the data science industry. These problems encompass a wide range of applications, from predicting sales and identifying patterns in market data to understanding movie plots and speech recognition. With recent advancements in data science, it has been observed that Long Short-Term Memory networks (LSTMs) are often the most effective solution for many sequence prediction tasks.

LSTMs offer certain advantages over conventional feed-forward neural networks and Recurrent Neural Networks (RNNs). They possess the unique ability to selectively remember patterns over long periods of time, making them well-suited for time-series forecasting tasks.

Conclusion and Future Prospects

In conclusion, this study has explored the potential of utilizing machine learning algorithms in wealth management systems to provide personalized financial advice and assistance. By leveraging clustering techniques and Prophecy, we have developed a system capable of effectively segmenting customers based on their risk levels and providing tailored investment recommendations.

Looking ahead, there are several avenues for future research and development in this field. Firstly, further refinement of the machine learning models and algorithms used in wealth management systems can lead to enhanced accuracy and performance in predicting investment outcomes. Additionally, incorporating real-time data feeds and advanced predictive analytics techniques can enable the system to adapt to changing market conditions and provide more timely and relevant recommendations to users.

Furthermore, expanding the scope of the system to include additional financial services and investment options can cater to a broader range of user needs and preferences. Integration with emerging technologies such as blockchain and decentralized finance (DeFi) could also open up new possibilities for innovation in wealth management.

Overall, the future of wealth management lies in harnessing the power of machine learning and AI to deliver personalized, data-driven financial solutions that empower individuals to achieve their financial goals effectively. Through ongoing research and development efforts, we can continue to advance the capabilities of wealth management systems and drive positive outcomes for users in the ever-evolving landscape of finance.

References

[1].Ibrahim M. Hamed, Ashraf S. Hussein, Mohamed F. Tolba, An intelligent model for stock market prediction, in the International Journal of Computational Intelligence Systems, 2012

[2]. P. Guo, M. Waqar, H. Dawood, M. B Shahnawaz and M. A. Ghazanfar, Prediction of Stock Market by Principle Component Analysis in 13th International Conference on Computational Intelligence and Security, 2017

[3].Z. Hu, J. Zhu and K. Tse, Stocks Market Prediction Using Support Vector Machine, in 6th International Conference on Information Management, Innovation Management and Industrial Engineering, 2013.

[4].S. Kavitha, S. Varuna and R. Ramya, A Comparative Analysis on Linear Regression and Support Vector Regression, in Online International Conference on Green Engineering and Technologies (IC-GET), 2016.

[5].Eric Alexander, Emily Kawaler, Dan Szafir, Stock Market Analysis and Prediction, 2011

[6].R. Verma, P. Choure and U. Singh, Neural Networks through Stock Market Data Prediction, in International Conference on Electronics, Communication and Aerospace Technology, 2017.

[7]. Agamloh, E., & Deb, S. (2022, October). Performance Comparison of Transverse and Axially Laminated Synchronous Reluctance Machines. In *2022 IEEE Energy Conversion Congress and Exposition (ECCE)* (pp. 1-7). IEEE. DOI: https://doi.org/10.1109/ECCE50734.2022.9947590

[8]. Jimmy, F. N. U. Understanding Ransomware Attacks: Trends and Prevention Strategies. DOI: https://doi.org/10.60087/jklst.vol2.n1.p214

[9]. Atacho, C. N. P. (2023). A Community-Based Approach to Flood Vulnerability Assessment: The Case of El Cardón Sector. *Journal of Knowledge Learning and Science Technology ISSN: 2959-6386 (online)*, *2*(2), 434-482. DOI: https://doi.org/10.60087/jklst.vol2.n2.p482

[10]. jimmy, fnu. (2023). Understanding Ransomware Attacks: Trends and Prevention Strategies. Journal of Knowledge Learning and Science Technology ISSN: 2959-6386 (online), 2(1), 180-210. https://doi.org/10.60087/jklst.vol2.n1.p214