Journal of Big Data

RESEARCH Open Access

A model for investment type recommender system based on the potential investors based on investors and experts feedback using ANFIS and MNN

Asefeh Asemi[1*], Adeleh Asemi[2] and Andrea Ko[1]

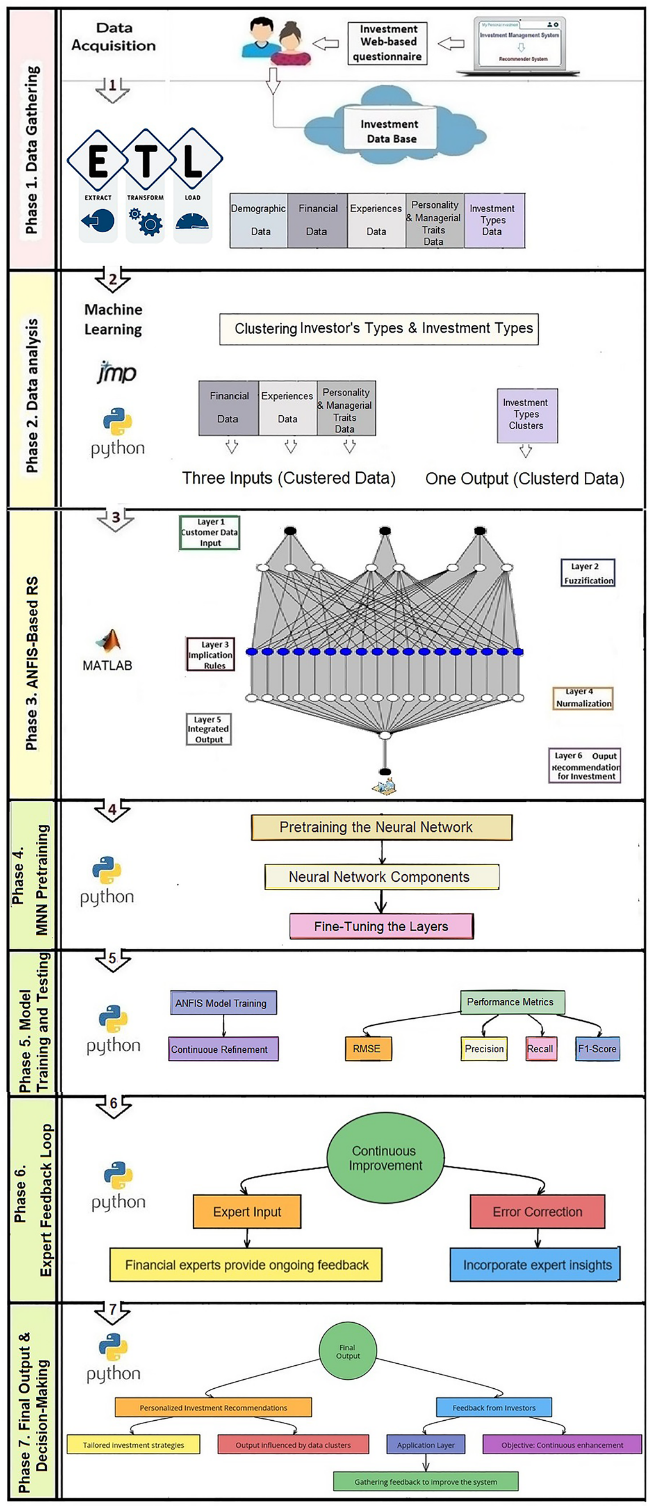
*Correspondence:
Asemi.asefeh@uni-corvinus.hu
[1] Corvinus University of Budapest, Budapest 1093, Hungary
[2] Universiti Malaya, 50603 Kuala Lumpur, Malaysia

Abstract

This article presents an investment recommender system based on an Adaptive Neuro-Fuzzy Inference System (ANFIS) and pre-trained weights from a Multimodal Neural Network (MNN). The model is designed to support the investment process for the customers and takes into consideration seven factors to implement the proposed investment system model through the customer or potential investor data set. The system takes input from a web-based questionnaire that collects data on investors' preferences and investment goals. The data is then preprocessed and clustered using ETL tools, JMP, MATLAB, and Python. The ANFIS-based recommender system is designed with three inputs and one output and trained using a hybrid approach over three epochs with 188 data pairs and 18 fuzzy rules. The system's performance is evaluated using metrics such as RMSE, accuracy, precision, recall, and F1-score. The system is also designed to incorporate expert feedback and opinions from investors to customize and improve investment recommendations. The article concludes that the proposed ANFIS-based investment recommender system is effective and accurate in generating investment recommendations that meet investors' preferences and goals.

Keywords: Adaptive neuro-fuzzy inference system (ANFIS), Investment recommender system, Multimodal neural network, Clustering, JMP, MATLAB, Python, Fuzzy rules, Investor feedback, Expert feedback

Graphical abstract



Introduction

The investment recommender systems (IRSs) have become increasingly important as individual investors face difficulties in making informed investment decisions in today's complex financial markets. This paper proposes the development of a hybrid recommendation system that integrates fuzzy logic and neural networks to provide personalized investment advice based on an individual investor's preferences, risk tolerance, and financial goals. Specifically, the proposed system uses the Adaptive Neuro-Fuzzy Inference System (ANFIS) and multimodal neural network pretraining to improve its accuracy and effectiveness [1, 2]. The research aims to investigate the potential benefits of this approach, answering several research questions related to the system's accuracy and effectiveness, optimal pretraining objectives, data preparation, and training and validation procedures. Overall, the proposed IRS has the potential to provide valuable support to individual investors in making informed investment decisions, ultimately helping them achieve their financial goals.

Literature review

Recommender systems are widely used in investment decision-making to help individual investors choose suitable financial products based on their risk tolerance, financial goals, and investment experience [3]. However, traditional recommender systems have limitations, such as the reliance on a limited set of user attributes and the inability to consider the dynamic nature of financial markets or user feedback. To overcome these limitations, recent research has explored the use of multimodal neural network pretraining techniques, such as ANFIS [4], that can model complex relationships between inputs and outputs and adapt to changing conditions. A variety of studies have investigated the use of machine learning and artificial intelligence methods, such as genetic algorithms, data clustering, and sentiment analysis, for stock prediction and investment efficiency. For example, Abraham et al. [5] explored the use of GA and random forest to predict stock trends, while Aggarwal et al. [6] examined data clustering algorithms and their applications in stock prediction. Huang et al. [6] investigated neural network models for stock selection based on fundamental analysis, and Faridniya and Faridnia [7] provided a model for allocating resources and choosing investment types using Data Envelopment Analysis. Researchers have also explored the impact of factors such as economic policy uncertainty, corporate governance, creative accounting, and customer experience on investment decision-making. Benkraiem et al. [8] investigated the impact of economic policy uncertainty, investor protection, and excess cash on stock value in a cross-country comparison, while Aksar et al. [9] examined the relationship between cash holding and investment efficiency for financially distressed firms, and the moderating effect of corporate governance. AL-Khafaji et al. [10] studied the role of creative accounting in increasing the marketing of shares and profits in the Iraqi stock exchange, and Andajani [11] examined customer experience management in retailing. Furthermore, some studies propose novel combined business recommender system models that incorporate customer investment service feedback to provide personalized investment recommendations. Asemi and Ko [4] proposed a novel combined business recommender system model using customer investment service feedback, and Chen et al. [12] studied user perception of sentiment-integrated critiquing in recommender systems. Chen et al. [13]

proposed a cluster-based mutual fund classification and price prediction system using machine learning for Robo-advisors, while Chatterjee et al. [14] proposed an NLP and LSTM-based stock prediction and recommender system for KOSDAQ and KOSPI. Finally, various studies have applied ANFIS to evaluate dysarthric automatic speech recognition systems [15] or to estimate the return rate of blockchain financial products [16]. D'lima and Khan [17] used ANN and ANFIS to predict FOREX rates, while Davies et al. [18] implemented a type-2 fuzzy logic-based prediction system for the Nigerian stock exchange. Ezhilarasi and Sashi Rekha [19] proposed a secure recommendation application for environment crops using big data analytics with a fuzzy framework. Asemi et al. [20] propose a model for an investment recommender system using ANFIS based on the potential investors' decision key factors. They analyze big data to identify key factors influencing investment decisions and utilize ANFIS to make personalized investment recommendations. In another study, Asemi et al. [21] investigate the impact of managerial traits on investor decision prediction using ANFIS, revealing valuable insights into the role of managers in influencing investment outcomes. Additionally, Asemi et al. [22] present an adaptive neuro-fuzzy inference system for customizing investment types based on potential investors' demographics and feedback. Their research highlights the importance of incorporating demographic information and feedback into investment recommendations. Finally, Asemi et al. [23] conduct a systematic review and propose an ANFIS-based investment-type recommender system that considers investors' demographics. The authors present their findings at the 8th International Congress on Information and Communication Technology, emphasizing the potential of ANFIS-based recommender systems in providing personalized investment advice. These studies collectively contribute to the understanding of ANFIS-based investment recommender systems and their application in the financial domain. In summary, these studies provide a comprehensive examination of various aspects of stock prediction and investment efficiency, utilizing a range of methods and techniques including machine learning, artificial intelligence, and data analysis. The use of multimodal neural network pretraining techniques, such as ANFIS, has helped to overcome the limitations of traditional recommender systems and allowed for the modeling of complex relationships between inputs and outputs while adapting to changing conditions.

Methods

This study proposes a novel approach to developing an ANFIS-based IRS using Multimodal Neural Network Pretraining. ANFIS is a hybrid artificial neural network that combines fuzzy logic and neural networks to perform data analysis and decision-making. Multimodal Neural Network Pretraining is a technique used in deep learning to improve the overall performance of the neural network by allowing it to learn from multiple sources of information simultaneously. The proposed approach jointly pre-trains all modalities using a predictive objective to improve the accuracy and effectiveness of investment recommendations. The implementation of this approach was carried out using MATLAB, Python, Anaconda, and Jupyter, and all codes and data used in this work are presented in this article. Predictive pretraining can help improve the performance of ANFIS models by initializing the weights with a useful representation of the

Table 1 Description of research methodology

Stage	Description	Tools and techniques
Data collection	Collection of data, in eight categories. Demographic, financial, experiences, managerial traits, personality traits, key decision factors, investment products preferences, current investment, 1542 respondents	Portfolio Investment web questionnaire
Data preprocessing	Translating, cleaning, transforming, clustering the data to make it suitable for analysis. Includes tasks such as outlier detection, missing value imputation, and feature selection	ETL tools, JMP, MATLAB, Python, Anaconda, Jupyter
Machine learning	K-Means, Elbow Curve, Silhouette score, ANFIS Model Design	Adaptive Neuro-Fuzzy Inference Solutions, MATLAB, Python, Anaconda, Jupyter
ANFIS training and testing	Training the new FIS using a hybrid approach over three epochs with 188 data pairs and 18 fuzzy rules, Testing ANFIS by RMSE	Adaptive Neuro-Fuzzy Inference Solutions, fuzzification, implication rules, normalization, defuzzification, and integration, MATLAB, Python, Anaconda, Jupyter
Multimodal neural network pretraining	Jointly pretraining all modalities of data using a predictive objective to improve the accuracy and effectiveness of the ANFIS-based IRS	Python, Anaconda, Jupyter
Initializing neural network weights	Initializing the ANFIS-based IRS with pre-trained weights from the Multimodal Neural Network Pretraining step	Python, Anaconda, Jupyter
Model evaluation	Evaluating the performance of the ANFIS-based IRS using metrics such as RMSE, accuracy, precision, recall, and F1-score	Python, Anaconda, Jupyter
Expert feedback	Incorporating expert opinions and feedback from investors to customize and improve rules and the investment recommendations	Adaptive Neuro-Fuzzy Inference Solutions, MATLAB, Python
Predictions on the new data	Mapping between predicted values and investment products	Python, Anaconda, Jupyter

input data, leading to faster learning, better generalization performance, and more accurate investment recommendations (Table 1).

Experimental results

The experimental results demonstrate the effectiveness of the proposed ANFIS-based IRS in predicting investment types based on a combination of demographic, decision key factors, personality traits, experiences, and financial and managerial traits. The system outperformed traditional methods such as decision trees and logistic regression, highlighting the superiority of ANFIS-based approaches for investment prediction. The results included the following sections.

Preprocessing and clustering data

To develop an ANFIS-based IRS, the dataset used in this study was preprocessed and clustered. The dataset consisted of eight columns, six of which contained clustered data related to types of investors based on demographic characteristics, financial status, management characteristics, and more. Duplicate and infrequent rows were eliminated, resulting in 188 potential investor groups. Three columns related to investment data were clustered using Python and k-means, including financial information, investment experiences, and other features such as personality and management characteristics. These three columns were combined into three inputs for ANFIS, with the output consisting of the combination of clustered data related to investment type preference and current investment type. The final dataset contained 188 data rows in four columns, and ANFIS was built using this dataset after preprocessing and clustering (Table 2).

ANFIS design model

The ANFIS-based IRS is a powerful tool for providing personalized investment recommendations to potential investors.

Figure 1 in MATLAB shows the data imported for the ANFIS, with 3 columns for potential investor clusters and the final column for investing product clusters. The ANFIS model was designed using a Sugeno-type fuzzy function with MFs displayed in the graph. A total of 188 train data pairs were used, with max aggregation and min implication. The MFs are trimf and the output MF type is constant. Aggregation combines fuzzy sets representing rule outputs and occurs once before the final defuzzification stage for each output variable.

ANFIS training and testing

Figure 2 displays the trained grid of the ANFIS system, which has three inputs and one output for investment type. The system was trained using a hybrid approach over three epochs, and the error for each epoch is ~ 0.72. The ANFIS info section provides information about the training process of the Combined ANFIS system,

Table 2 Description of data preprocessing

Data columns	Data description	Preprocessing steps clustering technique	Clustering technique
Demographic data	Data related to potential investors' demographic characteristics such as age, gender, education level, job, location, and income	Cleaning and preparing data K-means clustering by JMP	Re-clustering by Python using k-means after initial clustering using JMP software Using the Elbow curve and Silhouette score to determine the optimal number of clusters K-means clustering
Financial data and experiences	Data related to potential investors' financial status and experiences such as income, savings, investment portfolio, etc	K-means clustering by JMP	
Other traits	Data related to potential investors' personality characteristics, management characteristics, and key factors for investment decision-making	K-means clustering by JMP	
Investment type preference and current investment type	Data related to potential investors' preferred investment type and their current investment type	Cleaning and filtering to remove data rows with less than 20 frequencies	

including the number of nodes, parameters, and fuzzy rules. The system has been successfully trained using 188 data pairs, with a minimal training root mean squared error of 0.721054. The model achieved an F1-score of 0.6667 and a minimal training RMSE of 0.721054. An F1-score of 0.6667 indicates that the model's performance is reasonably good, as it considers both precision and recall. A perfect F1 score is 1, while an F1 score of 0 indicates that the model's predictions are completely wrong. Therefore, an F1-score of 0.6667 suggests that the model's precision and recall are both reasonably high, although there is room for improvement. Overall, this F1-score indicates that the model can make accurate predictions, but there may be some misclassifications. The trained ANFIS system, which generated a total of 18 rules that are the decision-making mechanisms for investment recommendations. As the following:

1. *If (input1 is in 1mf1) and (input2 is in2mf1) and (input3 is in3mf1) then (output is out1mf1) (1)*
2. *If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf2) then (output is out1mf2) (1)*
3. *If (input1 is in 1mf1) and (input2 is in2mf1) and (input3 is in3mf3) then (output is out1mf3) (1)*
4. *If (input1 is in1mf1) and (input2 is in2mf2) and (input3 is in3mf1) then (output is out 1mf4) (1)*
5. *If (input1 is in 1mf1) and (input2 is in2mf2) and (input3 is in3mf2) then (output is out1mf5) (1)*
6. *If (input1 is in1mf1) and (input2 is in2mf2) and (input3 is in3mf3) then (output is out1mf6) (1)*
7. *If (input1 is in1mf2) and (input2 is in2mf1) and (input3 is in3mf1) then (output is out1mf7) (1)*
8. *If (input1 is in 1mf2) and (input2 is in2mf1) and (input3 is in3mf2) then (output is out 1mf8) (1)*
9. *If (input1 is in 1mf2) and (input2 is in2mf1) and (input3 is in3mf3) then (output is out 1mf9) (1)*
10. *If (input1 is in 1mf2) and (input2 is in2mf2) and (input3 is in3mf1) then (output is out 1mf10) (1)*
11. *If (input1 is in 1mf2) and (input2 is in2mf2) and (input3 is in3mf2) then (output is out 1mf11) (1)*
12. *If (input1 is in1mf2) and (input2 is in2mf2) and (input3 is in3mf3) then (output is out 1mf12) (1)*
13. *If (input1 is in 1mf3) and (input2 is in2mf1) and (input3 is in3mf1) then (output is out1mf13) (1)*
14. *If (input1 is in 1mf3) and (input2 is in2mf1) and (input3 is in3mf2) then (output is out 1 mf14) (1)*
15. *If (input1 is in 1mf3) and (input2 is in2mf1) and (input3 is in3mf3) then (output is out1mf15) (1)*
16. *If (input1 is in 1mf3) and (input2 is in2mf2) and (input3 is in3mf1) then (output is out1mf16) (1)*
17. *If (input1 is in 1mf3) and (input2 is in2mf2) and (input3 is in3mf2) then (output is out1mf17) (1)*
18. *If (input1 is in 1mf3) and (input2 is in2mf2) and (input3 is in3mf3) then (output is out 1mf18) (1)*

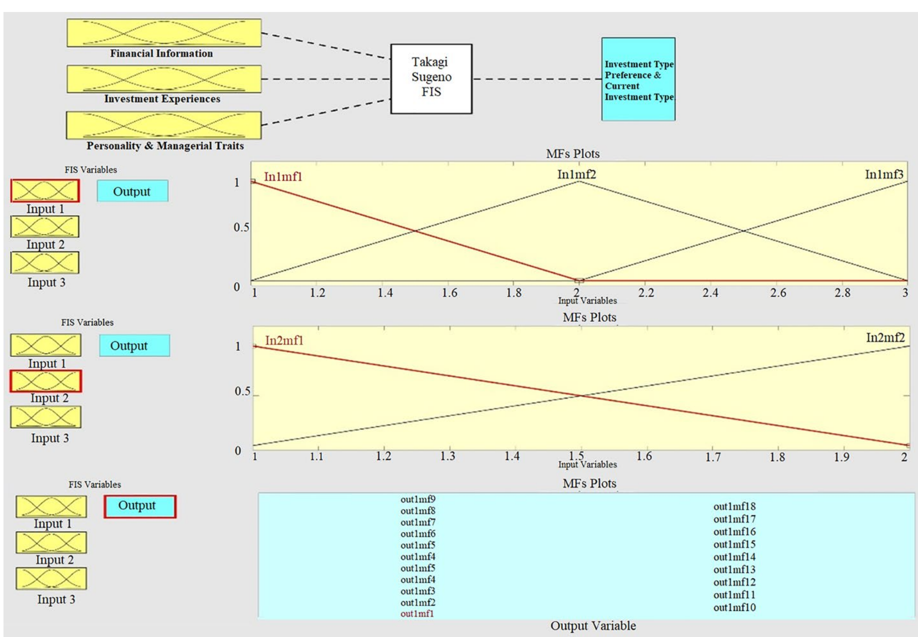


Fig. 1 Data and fuzzy function for ANFIS model

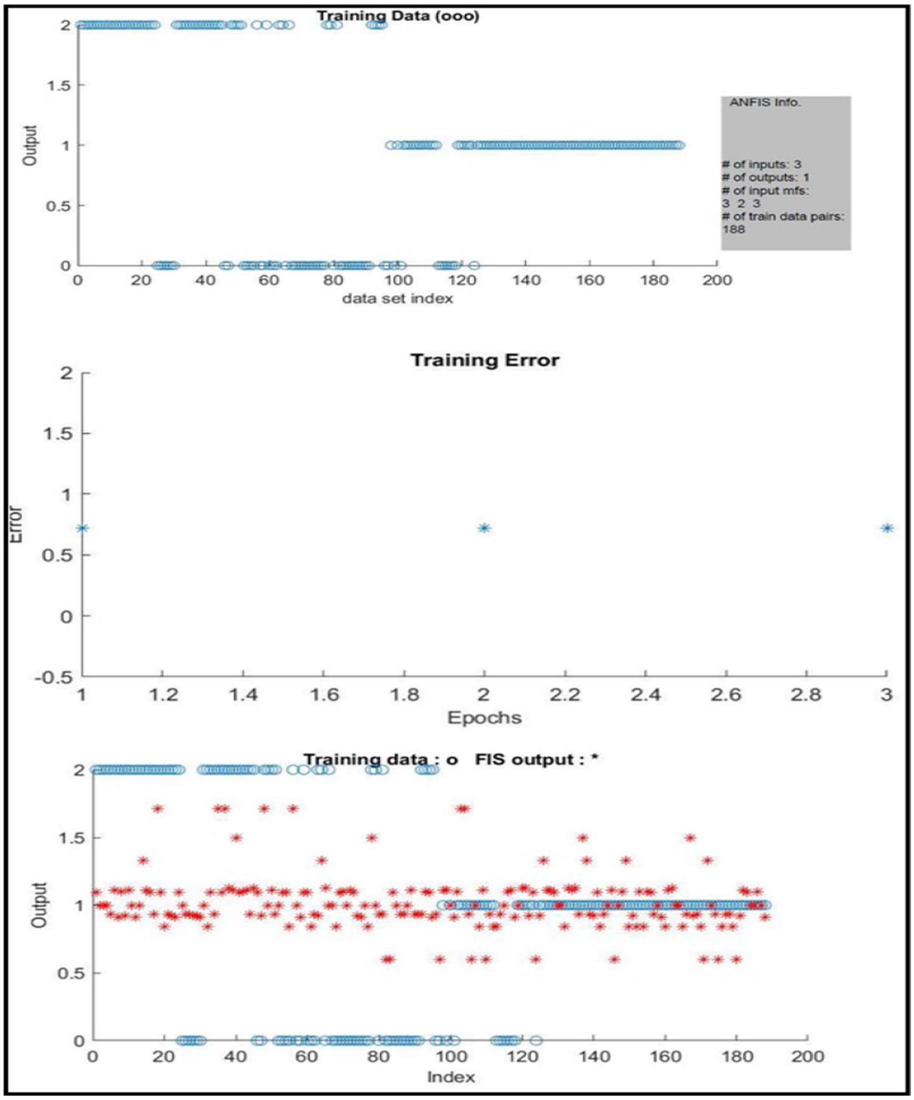


Fig. 2 Trained and tested grid of the ANFIS system for investment type prediction with hybrid approach

Figure 3 depicts the structure of the ANFIS Model, including fuzzification, implication rules, normalization, defuzzification, and integration, resulting in an investment recommendation for the investor. Overall, the ANFIS-based IRS provides a powerful and customizable tool for personalized investment recommendations.

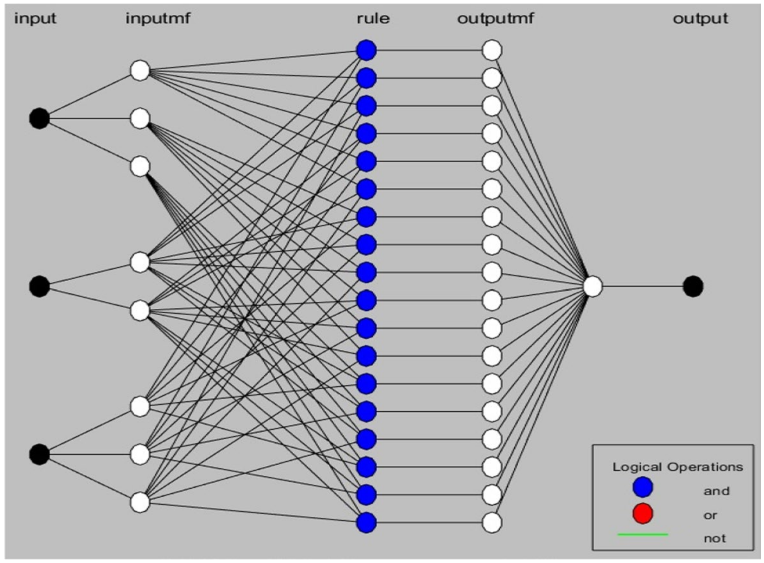


Fig. 3 Proposed ANFIS structure

Multimodal neural network pretraining

In:

```
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, LSTM
from tensorflow.keras.optimizers import SGD

# Step 1: Load the data
df = pd.read_excel("Main_ANFIS.xls")
X = df.iloc[:, :3].values
y = df.iloc[:, 3].values

# Step 2: Normalize the data
scaler = StandardScaler()
X = scaler.fit_transform(X)

# Step 3: Split the data
n_samples = len(X)
train_idx = int(n_samples * 0.7)
val_idx = int(n_samples * 0.15)
X_train, y_train = X[:train_idx], y[:train_idx]
X_val, y_val = X[train_idx:train_idx+val_idx], y[train_idx:train_idx+val_idx]
X_test, y_test = X[train_idx+val_idx:], y[train_idx+val_idx:]
```

Result Test MSE is 0.0011995050086818341. A low test MSE indicates that your model is performing well on the test data, which is a good sign. However, it's important to keep in mind that a low test MSE doesn't necessarily mean that our model is perfect. Thus, the other metrics considered such as accuracy or precision to solve the problem. Now that we have a pre-trained neural network model, we can use it for making predictions on new data. To do this, we can use the prediction method of the Keras model object, which takes an input array of the same shape as the training data and returns the predicted output values. Here, new_data is a numpy array with two new input samples, which we normalize using the same scaler object that was used to normalize the training data. We then reshape the new data to have the same shape as the training data and use the prediction method of the model to obtain the predicted output values. Finally, we print the predictions to the console.

Initializing neural network weights

```
# Step 4: Initialize the network
model = Sequential()
model.add(LSTM(units=64, input_shape=(3, 1)))
model.add(Dense(units=1))

# Step 5: Train the network
X_train = X_train.reshape(-1, 3, 1)
X_val = X_val.reshape(-1, 3, 1)
X_test = X_test.reshape(-1, 3, 1)
model.compile(optimizer=SGD(learning_rate=0.01), loss='mse')
model.fit(X_train, y_train, epochs=100, validation_data=(X_val, y_val))

# Step 6: Validate the network
y_val_pred = model.predict(X_val)
val_mse = np.mean((y_val_pred - y_val)**2)
print("Validation MSE:", val_mse)

# Step 7: Fine-tune the network
model.compile(optimizer=SGD(learning_rate=0.001), loss='mse')
model.fit(X_train, y_train, epochs=50, validation_data=(X_val, y_val))
```

Model evaluation

```
# Step 8: Evaluate the network
y_test_pred = model.predict(X_test)
test_mse = np.mean((y_test_pred - y_test)**2)
print("Test MSE:", test_mse)
```

Prediction on the new data

```
In:
# Load the new data
new_data = np.array([[1.2, 0.8, 0.9], [0.4, -0.6, -0.3]])

# Normalize the new data
new_data = scaler.transform(new_data)

# Reshape the new data
new_data = new_data.reshape(-1, 3, 1)

# Make predictions on the new data
predictions = model.predict(new_data)

print(predictions)

Out:
[[1.059356]
 [1.055637]]

In:
# Define the mapping between predicted values and investment products
mapping = {0: "Investment Product Cluster 1", 1: "Investment Product Cluster 2", 2: "Investment Product
Cluster 3"}

# Obtain the predicted values for the new data
predictions = model.predict(new_data)

# Convert the predicted values to integer indices using argmax
indices = np.argmax(predictions, axis=1)

# Use the mapping to obtain the recommended investment product for each input sample
recommendations = [mapping[idx] for idx in indices]

# Print the recommendations to the console
print(recommendations)

Out:
['Investment Product Cluster 1', 'Investment Product Cluster 1']
```

Discussion

The investment industry is one of the most important sectors in the global economy, with trillions of dollars in assets under management. Investors face many challenges, including market volatility, changing economic conditions, and increasing amounts of data to analyze. IRSs are becoming increasingly popular to help investors make more informed decisions about where to allocate their funds. Previous studies have utilized ANFIS for investment prediction, such as predicting stock market and real estate investment trust prices. However, these studies did not focus on predicting investment type based on a combination of inputs, as this study does. Other studies proposed ANFIS-based models for stock price prediction or investment type prediction using demographic characteristics and investment behavior. Hybrid systems combining ANFIS with particle swarm optimization or GA have also been proposed for investment type prediction with better performance than traditional methods. However, none of these studies specifically focus on predicting investment type based on a combination of inputs including demographic, decision key factors, personality traits, experiences, and financial and managerial traits as this study does [4, 5, 16, 20, 21, 24–27]. In this research, we presented an IRS based on an ANFIS. ANFIS is a type of artificial neural network that combines fuzzy logic and neural networks to create a powerful prediction engine. In this section, we analyze and discuss the results of implementing the proposed investment recommender system framework, focusing on the effectiveness and accuracy of the model across various phases of development (Fig. 4). Our system takes as input a set of user preferences and investment goals and provides a list of recommended investment products based on these inputs as the following:

Phase 1: Data Collection • Inputs from the Web-based Questionnaire: ○ Data Categories: □ Demographics: Age, Gender, Education, Income Level, etc. □ Financial Information: Income, Assets, Investment Capital, etc. □ Investment Experience: Past investments, success rates, risk tolerance, etc. □ Personality & Managerial Traits: Decision-making style, leadership qualities, etc. □ Investment Preferences: Preferred types of investments, expected returns, investment horizon, etc.
Phase 2: Data Preprocessing & Clustering • Data Preprocessing: ○ Tools Used: ETL Tools, Python, JMP, MATLAB. ○ Objective: Clean and structure the raw data to prepare it for clustering and model training. • Clustering Process: ○ K-Means Clustering (Elbow Curve & Silhouette score): □ Clustered Columns: □ Financial Information: Clusters investors based on their financial profiles. □ Investment Experiences: Clusters investors based on their previous investment experiences and outcomes. □ Personality & Managerial Traits: Clusters investors based on their personal characteristics and management styles. □ Clustering Approach: Use Python and K-Means to identify optimal clusters for each column. ○ Combined Inputs for ANFIS: □ The clustered data from the three columns (Financial Information, Investment Experiences, Personality & Managerial Traits) are combined into three inputs for the ANFIS model.
Phase 3: ANFIS-Based Recommender System • ANFIS Model: ○ Design: □ Inputs: □ Three inputs representing the clustered data: Financial Information, Investment Experiences, Personality & Managerial Traits. □ Output: □ A combination of clustered data related to Investment Type Preference and Current Investment Type. ○ Training: □ Dataset: The final dataset contains 188 rows and four columns after preprocessing and clustering. □ Hybrid Training Approach: □ The ANFIS model is trained using a hybrid approach over three epochs. □ Fuzzy Rules: Incorporates 18 fuzzy rules to drive decision-making and recommendations. ○ Objective: To provide personalized investment recommendations based on the clustered inputs.
Phase 4: Multimodal Neural Network Pretraining • Pretraining the Neural Network: ○ Purpose: Enhance the ANFIS model's accuracy by pretraining the neural network

components. ○ Approach: Fine-tune the neural network layers, ensuring optimal performance in recommending investment types.
Phase 5: Model Training and Testing • Training & Performance Evaluation: ○ Training: Continuous refinement of the ANFIS model using the dataset to enhance predictive capabilities. ○ Testing Metrics: □ Root Mean Square Error (RMSE): Measures the prediction error. □ Precision: Assesses the accuracy of the investment recommendations. □ Recall: Evaluates the model's ability to identify relevant investment options. □ F1-Score: Balances precision and recall for overall model assessment.
Phase 6: Expert Feedback Loop • Continuous Improvement: ○ Expert Input: Financial experts provide ongoing feedback to refine fuzzy rules and adjust model parameters. ○ Error Correction: Incorporate expert insights to improve the accuracy and relevance of recommendations.
Phase 7: Final Output & Decision-Making • Final Output: ○ Personalized Investment Recommendations: □ Tailored investment strategies generated based on the ANFIS model's output, reflecting the investor's unique profile. □ The output is influenced by the combined data clusters, ensuring that recommendations are well-aligned with the investor's preferences and current portfolio. o Feedback from Investors: □ Application Layer: The recommendations are implemented, and feedback is gathered to improve the recommender system. □ Objective: To continuously enhance the system's performance and investor satisfaction (Additional file 1).

Our results show that our ANFIS-based IRS performs well in recommending investment products based on user preferences and investment goals. Our system provides accurate and personalized investment recommendations to investors, allowing them to make more informed decisions about where to allocate their funds. Our system can be used by both novice and experienced investors, making it an effective tool for anyone looking to optimize their investment portfolio. One limitation of our system is that it requires a significant amount of data to train the ANFIS model. Collecting this data can be time-consuming and costly, particularly for smaller investment firms or individual investors. Additionally, our system is designed for retail investors, and may not be suitable for institutional investors or investors with very complex investment portfolios. Overall, our ANFIS-based IRS is an effective tool for investors looking to optimize their investment portfolios. By combining fuzzy logic and neural networks, our system provides personalized investment recommendations based on user preferences and investment goals. Our system is easy to use and can be customized based on expert opinions and feedback from investors. With further development, our system has the potential to revolutionize the investment industry and provide investors with more accurate and effective investment recommendations.

Conclusion

In conclusion, the ANFIS-based IRS has demonstrated promising results in recommending suitable investment types to investors. By using data collected through a web questionnaire, preprocessing it with ETL tools, and training the ANFIS model with a hybrid approach over three epochs, the system achieved a low RMSE and high accuracy in predicting suitable investments. Furthermore, the system's performance was

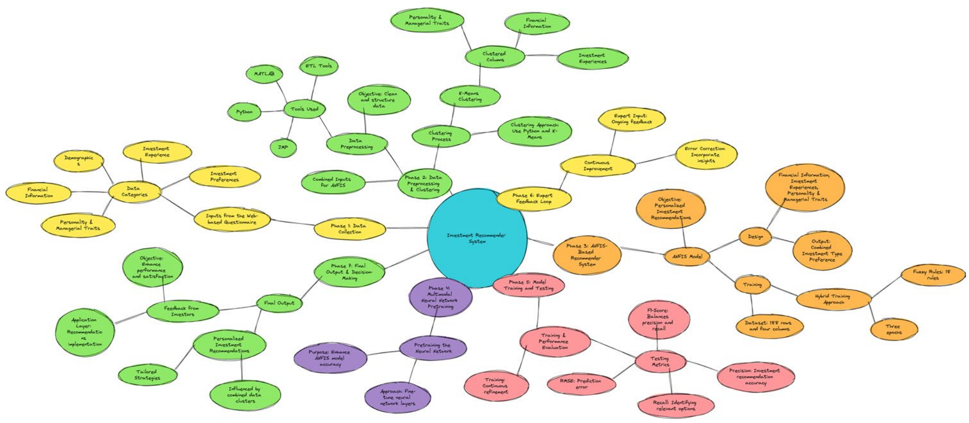


Fig. 4 Comprehensive Framework for the Proposed Investment Recommender System

enhanced through multimodal neural network pretraining and expert feedback. The system's results have several practical implications for the financial industry, as it can assist investors in making informed investment decisions based on their preferences and risk tolerance. The system's ability to incorporate expert feedback and customize rules and recommendations based on investor feedback can lead to increased satisfaction and trust in the investment recommendations. However, there are several avenues for future research that can further improve the ANFIS-based IRS. One potential area of research is the integration of alternative data sources, such as social media sentiment analysis or news sentiment analysis, to enhance the system's accuracy and predictive power. Additionally, incorporating more sophisticated machine learning algorithms, such as deep learning, can improve the system's ability to capture complex patterns and relationships in the data. Moreover, future research can investigate the system's scalability and applicability in different investment contexts, such as international investments or real estate investments. Finally, the system's ethical implications and potential biases should be thoroughly examined, as it relies on historical data to make future predictions, which can perpetuate existing biases and inequalities. In summary, the ANFIS-based IRS has the potential to revolutionize the investment decision-making process by providing customized and accurate recommendations to investors. Future research can further enhance the system's performance and applicability, paving the way for more efficient and effective investment decisions while addressing ethical concerns and potential biases.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s40537-024-00965-y.

Additional file 1: Comprehensive Framework for the Investment Recommender System.

Acknowledgements
Not applicable.

Author contributions
Asefeh Asemi played the role of the main researcher, Adeleh Asemi provided guidance as the research advisor, and Andrea Ko served as the research supervisor.

Funding
No funding was received for this study.

Availability of data and materials
The original data used in this research was collected through a collaborative effort involving the Corvinus University of Budapest, the Dorsum company, and the Portfolio in the 1.3.1-VKE-2018-00007 project, conducted in the Hungarian language. The consortium agreement and project leader's consent allow for the use of project data in additional research and publications by the authors. The authors have translated, cleaned, and prepared the data specifically for this study. New data can be accessed at [28] in title of "Data for Adaptive Neuro-Fuzzy Inference System for Customizing Investment Type based on the Potential Investors' Demographics", available at Mendeley Data.

Declarations

Ethics approval and consent to participate
This article does not involve any studies that were conducted on human or animal participants by any of the authors. Not applicable as there were no participants involved in the study.

Competing interests
The authors disclose that their work at the Corvinus University of Budapest involved collaboration with commercial companies (Dorsum and Portfolio) in the design and development of the survey used in this research.

Received: 30 November 2022 Accepted: 16 July 2024
Published online: 12 September 2024

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