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Bridging AI and Emotion: Enhanced Models for Personal Finance Manager Applications

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This paper focuses on creating and deploying an innovative Financial Advisor Application that would revolutionize conventional financial planning methods with the help of state-of-the-art artificial intelligence tools and effective financial services. Indeed, the essence of this application is user-oriented and focuses on creating more ways to engage the user and help them make the right decisions by redesigning the interface and providing individualized financial guidance. The application combines different aspects of financial management, including budgeting, transaction tracking, and goal setting, but also sees novelties as an artificial intelligence function that detects anomalies in transactions and the merchant offers explicitly created for clients. The technical structure involves access to data, the description of each module, and the use of AI that provides anticipatory analysis and tools for advanced financial planning. Business testing and vulnerability assessments were performed several times, proving the business value and reliability of the application, thus avoiding data leakage and modularity viruses. The paper assesses the effects on the users' satisfaction when provided with such technologies and their ability to change their financial management behavior, therefore providing an exhaustive scenario of the credentials of AI for improving the efficacy of financial advisory. The conclusions released in the paper should advance knowledge of financial technology as it demonstrates how the intelligent systems used in a presented application can lead to noteworthy improvements for both users and financial companies by offering advanced financial recommendations automatically and presciently.

1. Introduction

The Financial Advisor Application is a perfect example of the synergy of highly developed IT solutions and profound financial knowledge in the constantly evolving field of fintech. This application revolutionizes personal finance management by utilizing advanced AI along with a plethora of financial products and services that are unique to the clients. Unlike traditional instruments that work independently of one another, this platform offers a global picture of a person's financial status and provides recommendations and solutions.

Due to the advanced semantic AI, the Financial Advisor Application is proficient in identifying users' emotions regarding financial activities and textual information. This advanced feature allows the application to provide more personalized financial advice and emotional support, making the financial management process more accessible and sensitive. As the program determines the user's emotional state when making financial decisions, the application offers recommendations that match the feelings and objectives of the user, thus increasing the interest and satisfaction of users.

Also, constant transactions are controlled by the application through highly developed anomaly detection algorithms. This security feature quickly detects any suspicious activity associated with fraudulent activities, thus protecting users' financial resources. The anomaly detection ability protects the money and makes users aware of standard spending patterns to avoid risking their money.

Apart from these features, the application also customizes the shopping experience by identifying the merchants with whom the users have transacted. This feature provides a user-friendly experience and can save the most money by recommending discounts and promotions from associated sellers. Thus, the Financial Advisor Application dictates that users get only the best deals by considering past purchases and preferences, promoting financial optimality and customer happiness. It questions the conventional business models of financial consulting and modernizes the principles of the personal finance industry. It gives an insight into the prevailing position of the application of AI in the financial sector, which opens up future financial decision-making as informative, inclusive, and innovative. When reflecting on the possibilities and features of the Financial Advisor Application, it is crucial to realize that this is not merely an application but a financial assistant that helps users in their economic endeavors with accuracy and wisdom [1-3].

2. Problem Statement

This desire for more effective tools to extend financial consultancy with the help of the internet and mobile applications highlights the necessity of stable methods to

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develop individual, particular approaches for every user. Most contemporary approaches to managing financial and accounting activity are based on fixed structures that ignore essential data, including general user behavior and attitude, which are needed to define what kind of recommendations the administrators should give. The problem is that these applications become mere carriers of simple data transfers and cannot analyze user data such as frequency, mood, and preferences crucial to providing timely financial assistance.

Furthermore, today's financial platforms can also process structured data effectively. Still, they cannot extract as much value as from the unstructured data that stems from inputs about the users and descriptions of the transactions [4]. This can lead to recommending other products or services that the user does not need or cannot handle emotionally, thus limiting the possibility of positive interaction and satisfaction. Specifically, it has been found that studies on concrete applications of the soft computing paradigms, like the applications with semantic analysis or the applications that include adaptive learning mechanisms, help solve the problems of financial advising. However, the practical application of these complex methods requires effort.

Regarding the above issue, a reasonable suggestion for improvement is to combine TensorFlow and Keras with a Python environment. This integration will help the application learn the users' activities and preferences by integrating semantic AI and M-learning solutions. Thus, achieving these objectives will facilitate the receipt and analysis of transactional data such as the number of transactions, the frequency of transactions, the currency, and any other quantitative indicators. It will also process inputs that contain quality or quantity data, such as the quantity of product, the quality of material, and so on. The knowledge of the users' requirements will be constructed by applying artificial neural networks in this application. This functionality can give general information concerning financial conduct and give particular recommendations depending on the user's data, significantly increasing user satisfaction.

This study will seek to fill the gap between conventional financial advisory platforms and advanced AI-based solutions by developing a financial advisor application that analyzes, comprehends, and responds to each user's economic story. This approach solves the crucial problem of improving the quality and effectiveness of digital services' financial recommendations, which raises users' confidence in financial planning applications.

3. SCOPE OF WORK

This project is wholly devoted to the user. Our vision is to create a highly sophisticated Financial Advisor Application as a service and a sidekick in the financial life. This work involves leveraging the features of NET Core 6 to design an extremely robust and highly scalable application. We have integrated advanced features of AI in Python, which are generally used for deep learning, such as anomaly detection, consecutive transaction prediction, and semantic analysis [5]. Thus, using this diverse approach, we aim to enhance your experience on the site by providing timely and accurate information on managing money. This project has been developed with the needs of user experiences in mind.

It is also not simply a matter of incorporating the different and complex aspects of modern financial advisory services' features into the application's architecture. It is about developing a framework that is open and capable of changing according to the conditions of the field. Abstract classes define the application structure, and this decision makes it possible to add new features and change the product's behavior without affecting its essential characteristics by third parties.

Implementing AI and machine learning into the application is not just a technicality. It's a strategic decision to address three primary objectives: Anomaly detection for better transaction security, predictive analysis for better financial decisions, and semantic analysis for better financial planning advice.

Among them, the most important is to develop and optimize deep learning models for detecting anomalies in financial transactions. Python and other necessary machine learning libraries will be used to create the application that will assist in identifying suspicious activity and increasing transaction security. We know how critical security and reliability are in financial applications and strive to provide you with a product you can rely on.

To develop predictive models for financial forecasting: Using historical data of financial records and the user's transaction history, the application will give the prognosis of a specific financial outcome and assist the user in making the correct economic decision.

To incorporate semantic analysis for understanding user sentiment and behavior, the application will use NLP techniques to better understand user inputs and feedback and provide more accurate and practical financial planning recommendations based on the client's emotional status.

The research questions guiding the development of this application are:

In what ways can deep learning models be used to solve the problem of identifying anomalous transactions? NET Core 6 environment?

What methods can be used to effectively forecast financial patterns and users' actions based on transactional data using Python-based AI tools?

4. LITERATURE REVIEW

The spread and development of fintech have fostered further development of new applications that would contribute to the simplification of financial transactions and increase the accuracy and personalization of the offered financial recommendations. Among these innovations, the Financial Advisor Application is one of the best integrated and sophisticated applications in the world of technology. This paper aims to provide a literature review to establish the essential technologies and critical applications that define this revolutionary application. This new financial advisory tool combines contemporary computational techniques with traditional but customized services.

A. Comprehensive Financial Overview

The application gives users a summary of the financial situation, combining the data from several accounts and the asset summary, liability, expenditure, and savings plan. Users can make sound financial decisions by offering precise and concise financial decisions since the application provides a clear and concise financial picture. This feature corresponds with Anderson (2019), who states that data integration and visualization play a crucial role in improving user experience and their decision-making process [4].

B. Technological Base and Management Framework

As stated earlier, the basis of the described Financial Advisor Application is the use of .NET Core — a decision that signals the readiness to build solid and scalable apps [6]. NET Core is a highly adaptive, fast, and secure platform crucial for financial applications involving users' data. It ensures that complex capabilities are closely integrated and the application will not slow down or have issues with various loads. This is especially the case within the financial services industry, where the accuracy of data and its authenticity cannot be compromised.

It is integrated with NET Core, and the application utilizes Python's AI features, including TensorFlow and Keras. These libraries are among the most advanced tools for deep learning, which can analyze enormous amounts of information successfully and search for valuable information. Consequently, the use of the two has become mixed up. NET Core for structure and Python for intelligent operations are the best pairs that bring high efficiency and intelligence to the Financial Advisor Application.

C. Future Directions and Research Opportunities

Thus, the application of AI in financial advisory services offers many potential research avenues, especially regarding the protection of users' data, the usage of responsible AI, and the suitability of AI in financial decision-making. Future research could focus on the effects of real-time data analysis on economic forecasting, the utilization of AI to improve financial awareness, and how best to increase the degree of customization of financial advice using more sophisticated machine learning algorithms.

Moreover, the application's architecture and features allow for integrating quantitative and qualitative sentiment analyses of financial statements. Thus, perpetuating the integration of these elements can lead to further efficiency and customization in economic consulting.

The Financial Advisor Application is a new generation of personal finance management tools that incorporate the best features. Based on NET Core 6 and AI technologies developed using Python, it will be possible to provide users with a powerful, safe, and highly customized experience [6]. The application stands out from other financial technology applications through its capacity to predict trends, identify deviations from standards, and analyze user sentiment. The continued advancement of the application will give a glimpse of the possibilities and difficulties of using AI in delivering effective and efficient financial services to users, propelling the development of better and more effective user-oriented financial technologies.

D. Semantic analysis for improving the user experience

The model of interaction between the user and the financial applications is in the concept of semantic analysis [7]. Thus, the application can respond and give recommendations much closer to the user's expectations and emotions based on the context and details of the user's questions and statements. This level of understanding is basic in creating the foundation of trust and interest from the user as it gives a system that is prepared to listen and adapt to the user. Technologies in the context of semantic AI within the Financial Advisor Application enhance overall user satisfaction because the system is more responsive to the users' needs and concerns regarding their finances.

E. The Relationship between Deep Learning and Machine Learning

The programming tools most useful for machine learning in Python are TensorFlow and Keras, which can predict financial trends, detect anomalies, and analyze semantics [8]. These capabilities enable the application to detect transaction patterns, predict the users' future economic activities, and ascertain their needs. RNNs will do the data analysis, and insights and recommendations will be given with the help of data analysis. However, very subtle patterns in the data may not be easily detected.

Substantial evidence suggests that machine learning models should be incorporated into financial forecasting. For example, models help predict market trends and identify patterns humans may not notice. These capabilities are crucial for creating a predictive financial advisory setting that responds to the user's data shift.

F. Anomaly Detection and Security

Another critical aspect of the Financial Advisor Application is the functionality for identifying irregularities in the user's actions. Artificial intelligence and machine learning within the application allow it to look for irregularities that may indicate fraud [8]. Such an approach to security means that the users can input their financial details into the application safely, knowing that any fraudulent activity will be quickly identified. Machine learning helps improve transaction security, which is essential for users' confidence and applications' authenticity.

The two areas of application of Business Analytics are Predictive Analytics and Financial Forecasting.

Financial Advisor Application uses state-of-the-art predictive analysis to help users predict the financial future. Historical data and current transactions help predict future spending, income, and potential financial troubles. This allows users to make decisions, make expenditures, and achieve goals since they know what to expect in the future.

G. Customization and Extensibility

When it comes to extensibility and customization, the application's architecture, especially the usage of abstract classes, serves as a guideline [9]. This architectural decision enables third-party developers and financial institutions to extend the application's core functionalities to suit different needs while not risking the overall integrity of the application [9]. It is a strategic move that centralizes the needs of a global user base and the required financial regulations, languages, and operational customizations.

This flexibility is essential to keeping the application up to date and effective in a rapidly evolving financial environment provided by abstract classes. This aligns with research by Tertilt and Scholz, who postulated that financial solutions must be flexible enough to suit users' needs.

H. Personalized Financial Advice

Personalization is the foundation of the Financial Advisor Application's proposition. Thus, the application can provide recommendations consistent with the user's spending patterns and financial objectives through semantic analysis and predictive models. Whether it is about saving money, investing money, or even planning for the budget, the application is designed to help according to the particularity of the user. This level of personalization is accomplished through learning and development to ensure that the advice is ever helpful and efficient in the future.

I. AI-Driven Merchant Recommendations

For better user experience and more savings, the Financial Advisor Application also uses Artificial Intelligence to analyze users' transaction history and suggest merchant offers. This not only helps the consumer by making the experience more personal and tailored to their needs but also helps them save money with discounts and sales from the partnered vendors. The application also employs user data and artificial intelligence to provide users with the most enriching offers, thus giving value to their financial operations.

J. AI Predicting Trends

It has been proved that AI can perform very well in predictive solutions across different domains, particularly financial platforms. Historical data are significant because AI computers can find hidden patterns that human analysts may otherwise ignore. Deep learning and neural networks have been critical in helping identify these patterns. For instance, Rezaei et al. (2020) have described how deep learning algorithms can perform the stock market's future downtrends with a high accuracy level, which can be helpful for investment [11].

K. AI in Other Fields

Although AI is particularly incorporated in finance, it resonates in multiple industries. In healthcare, AI algorithms are used for outbreak prediction and deep learning is utilized to design individual patients' care plans [12]. In the same way, in retail, AI is used to keep track of the stock and make recommendations to customers [13]. These advancements also indicate that AI has the unique ability and capacity to tailor applications to revolutionize several industries and sectors [15] [16].

L. AI and Sentiment Analysis

Considering the growing popularity of AI applications in various industries, it is paramount to explore customer sentiment analysis. It typically marks text mining techniques that seek to identify the tone of opinion users express. This technique finds broader usage in the financial world for ascertaining the market mood from news articles and tweets. A listing by Bollen et al. (2011) revealed that the mood on Twitter could affect the movements of the stock market, making sentiment analysis crucial in market analysis.

M. Behavior Prediction:

Customer behavior prediction using artificial intelligence includes identifying patterns and definitions of behavior to make assumptions about the likely behavior of customers in the foreseeable future. This is particularly helpful in marketing with personalized segments and customer maintenance programs. For instance, there are behavioral prediction models to determine which customers are most likely to churn, and businesses can take preventive measures [14]. This capability is also essential in processing financial expenditure since spending behaviors can provide valuable insights into financial management advice [17].

N. *Forecasting*

AI has enormously changed the different sectors through the foresighted analysis of the data collected. Some models, such as the LSTM and N-BEATS, have been used in finance studies, as shown in the time series forecasting. Such models can deal with intricate data patterns and offer robust prediction, which can help make decisions [18, 19].

Therefore, there is enough ground for integrating machine learning models in financial forecasting. For instance, models aid in comprehending attitudes and climates that humans may not discern inherently. These capabilities are essential for constructing an accurate advisory financial environment that adapts to the alteration of data mentioned by users [11，19].

O. *AI in Natural Language Processing*

The developments in natural language processing (NLP) have contributed immensely to improving the capability and capacity of various forms of AI to interpret and create natural languages. These enhancements have ensured a better handling of user interactions and an excellent sentiment analysis. It is essential to discuss deep learning trends in NLP, the progress made, and the future that may lie ahead for these technologies, which was addressed by Young et al. in the perspective of 2018 [20].

5. METHODOLOGY

The research method involved using complex machine learning and Artificial intelligence to offer personalized financial advice based on the bank's transactions. The first and foremost purpose was to understand customers' moods, detect any abnormality in the transactions, and provide merchants with the appropriate discount based on the customers' activities. This was accomplished through semantic analysis, predictive analytics, and anomaly detection [9].

A. *Dataset*

The records in this analysis were obtained from bank transaction histories grouped into Visa and Mastercard Merchant Categories (MCC). These categories are essential in establishing trends and patterns where customers will likely spend their money. The dataset included the following components:

Transaction Data: Transaction logs include the transaction amount, date, and MCC codes.

Merchant Data: Other details concerning merchants classified by Visa and Mastercard help understand users' spending habits [4].

	CategoryId	CategoryN...	mccfrom	mccto	id
▶	1	Government...	9000	9999	1
	2	Retail Outle...	5000	5599	2
	3	Airlines	3000	3299	3
	4	Contracted ...	1500	2999	4
	5	Miscellaneo...	5700	6009	5
	6	Clothing St...	5600	5699	6
	7	Professional...	8000	8999	7
	8	Lodging	3500	3999	8
	9	Transportati...	4000	4799	9
	10	Cash	6010	6011	10
	11	Business Ser...	7300	7999	11
	12	Utility Servi...	4800	4999	12
	13	Car Rental	3300	3499	13
	14	Agricultural ...	0001	1499	14
	5	Miscellaneo...	6012	7299	15
*	*NULL*	*NULL*	*NULL*	*NULL*	*NULL*

Figure 1 : MCC

a) *Transaction Data*

Tables: dbo.Customer_Cards, dbo.Extraaccounts, dbo.Extratransactions, dbo.Finance_Category, dbo.Finance_SubCategory, dbo.Finance_MainCategory, dbo.Finance_Goal_MainCategory, dbo.Finance_Goals, dbo.Finance_Budget, dbo.Budget_Category.

Description: Detailed records of user transactions, including transaction amount, date, and MCC codes. These transactions span various categories like dining, travel, retail, and more, providing a comprehensive view of user spending.

Use Case: This data helps understand user spending behavior, which is critical for predicting future transactions and identifying anomalies.

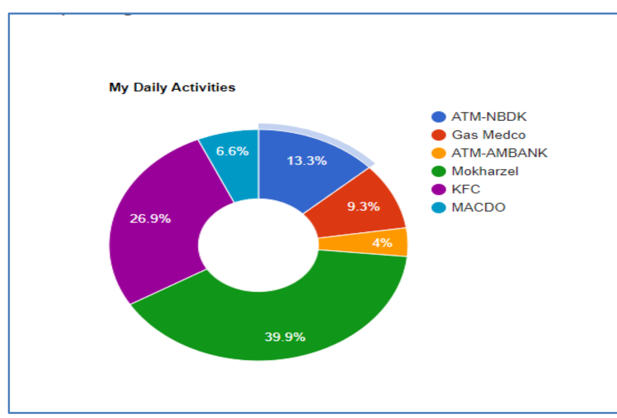

Figure 2 : Dashboard

b) *Merchant Data*

Tables: dbo.Merchant_List, dbo.Merchants, dbo.Merchant_Suggestion, dbo.Merchant_GiftCard, dbo.Merchant_Promotion, dbo.Merchant_Rewards, dbo.Merchant_Category, dbo.CustomerType_Merchant.

Description: Information about merchants categorized by Visa and Mastercard. This includes details about the types of merchants frequented by users and the offers available.

Use Case: Helps provide personalized merchant recommendations and discounts based on user transaction history.

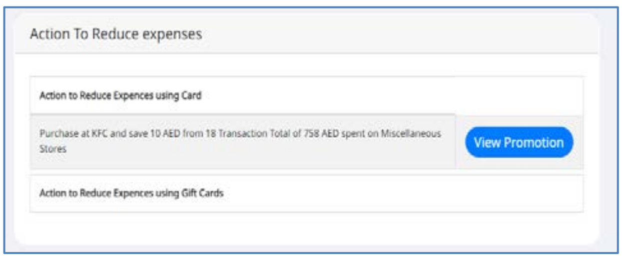

Figure 3: Suggestions

Figure 4: Merchants

c) Account Data

Tables: dbo.Extraaccounts, dbo.Customer_user, dbo.Extratransactions, dbo.Finance_Budget, dbo.Budget, dbo.CardsProducts, dbo.CardsTypes, dbo.Cards_Cashback.

Description: Includes data about users' account balances and activities, such as savings, checking, and investment accounts. Monitoring these accounts helps in setting realistic financial goals and budgeting.

Use Case: Essential for creating comprehensive user profiles and providing accurate financial advice.

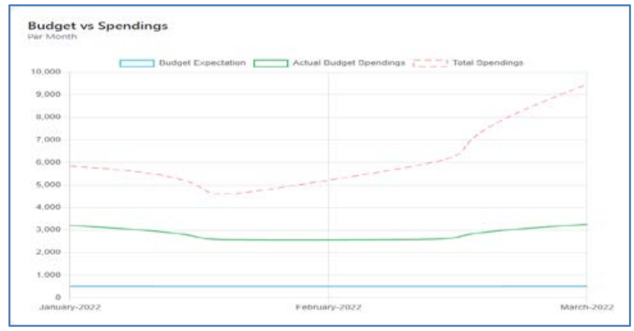

Figure 5: Spending Behavior

d) User Profiles

Tables: do. Customers do.Customer_user, dbo.PersonalInfo.

Description: Detailed profiles for each user, combining their transaction history and account data, including demographic information, spending habits, income levels, and financial goals.

Use Case: Provides the foundation for personalized financial advice and recommendations.

e) Anomaly Detection Data

Tables: dbo.ML_Transactions_anomalies.

Description: Data for identifying irregular transactions that may indicate fraud or unexpected behavior. This table stores information about detected anomalies.

Use Case: Enhances transaction security by identifying and alerting users of potential fraudulent activities.

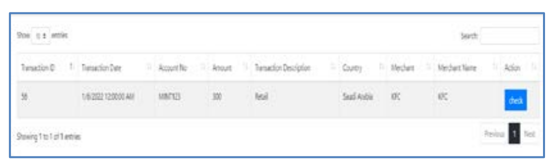

Figure 6: Anomaly Transaction

f) Budget and Goals

Tables: dbo.Finance_Budget, dbo.Budget_Category, dbo.Finance_Goals, dbo.Finance_Goal_MainCategory.

Description: Information about users' budgets and financial goals. This includes the categorization of expenses and the tracking of progress towards financial targets.

Use Case: It helps users set and manage financial goals and budgets, ensuring they stay on track with their financial plans.

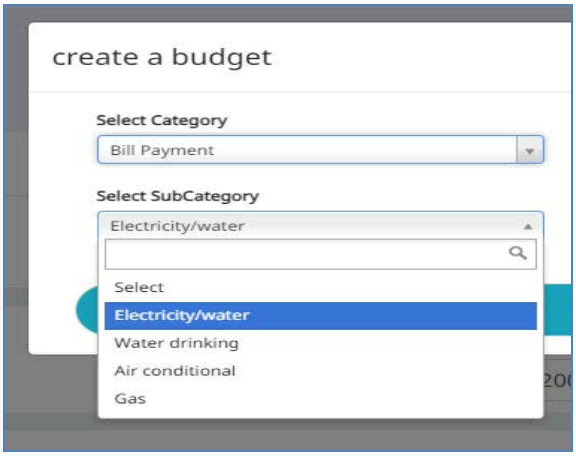

Figure 7: Budget creation

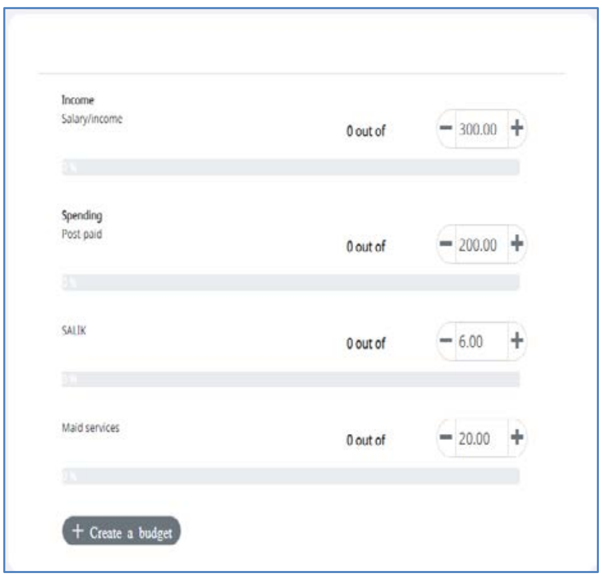

Figure 8: Budget Widget

Figure 9: Budget Dashboard

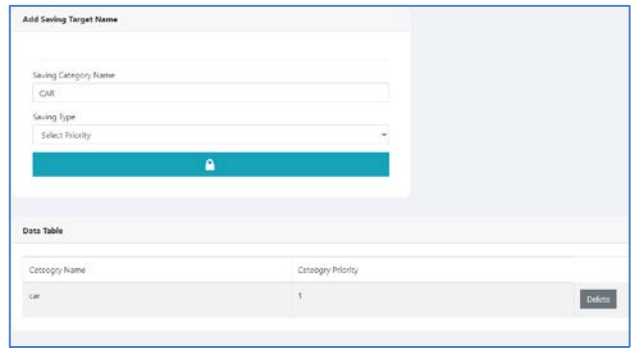

Figure 10: Goal Creation

B. *Sentiment Analysis and Data Integration*

This is an essential component of the Financial Advisor Application as it categorizes customers' emotions according to their transactions. This process is necessary to analyze the user's behavior and recommend financial decisions. This section reports a detailed plan on how the study will conduct the sentiment analysis and integrate data [3].

a) Preprocessing

Data Cleaning: Transaction descriptions were preprocessed to eliminate noise and ensure that all the entries were in the same format. This step included preprocessing the text by adjusting common formatting issues, including punctuation, capitalization, and spelling errors.

Normalization: The transaction amounts and dates were scaled to a manageable level to enable their use in the analysis. This was done to standardize the results by either using the current US dollar exchange rate or inflating the amount to the current year if necessary.

b) Training

Language Models: To determine whether each transaction description is positive, negative, or neutral, we employed pre-trained language models specialized in financial data for sentiment analysis on the cleaned transaction descriptions. These models included BERT and GPT, which were fine-tuned on a financial text corpus to enhance the model's performance on context-dependent terms.

Classification: Based on the nature and details of the transaction descriptions, these transactions were then divided into a set of pre-determined emotional types, namely Outgoing, Sad, Feeling Generous, Shopping, Roadtrip, Adventurous, Health-Focused, Stressed, Culturally Engaged, and Tech Enthusiast.

c) Integration

Sentiment Scores: The sentiment of each transaction was then determined based on the emotion associated with it. These scores were then compiled and computed over various intervals to give insights into the user's emotional patterns.

Profile Enrichment: The sentiment scores were combined with other user data, such as transaction history and account details, to augment the user profiles. This integration provided a more comprehensive picture of the user's financial activity.

Contextual Analysis: This would have the added advantage of complementing numerical data and the findings from sentiment analysis in a way that was impossible through conventional statistical modeling. For instance, many small purchases interspersed with more significant amounts could indicate that the person is spending money due to stress.

d) Personalized Insights

Behavior Prediction: By combining the data, the application could suggest how the user will spend money in the future and give recommendations. For example, a user in the Health-Focused segment will be given suggestions for membership in a fitness club or other health offers.

Anomaly Detection: The sentiment analysis also highlighted possible abnormalities. For instance, an abrupt change in spending behavior from a user classified as Risk-Averse to high-risk spending would prompt an alert.

Merchant Recommendations: It could even recommend merchants based on people's emotional trends and spending habits. For example, users categorized as Adventurous might be offered specific coupons and deals on products from subscribed merchants that fall under the travel category.

e) Feedback Loop

User Interaction: Users could engage with the application by confirming or disputing the sentiment categorizations. This feedback process helped improve the models and increase the precision of the predictions over time.

Continuous Learning: These sentiment analysis models were refined using user feedback and fresh transaction data incorporated into the system.

The Financial Advisor Application incorporated sentiment analysis and information about the user's transactions and accounts, allowing for sophisticated and feasible recommendations. This created a holistic approach that helped to provide users with recommendations and insights backed by data and, at the same time, could consider the emotional context of the situation.

C. Predictive Modeling

We used sophisticated statistical tools to forecast future spending patterns and recommend proper financial management. These models were meant to evaluate past financial transactions to predict future actions. Here's a detailed breakdown of our approach to predictive modeling: Here's a detailed breakdown of our approach to predictive modeling [10].

a) Model Selection

We selected three primary predictive analysis models: Transformer Models, Temporal Convolutional Networks (TCN), and N-BEATS. Each model has distinct advantages in handling time-series data and capturing various aspects of financial behavior.

b) Transformer Models

Architecture: Transformer architectures efficiently learn long-term dependencies inherent in data and thus do not require sequential computations, making them suitable for time series prediction. They employ self-attention mechanisms that determine the relevance of different points in a sequence.

Implementation: The Transformer model was developed using TensorFlow/Keras. It comprises several stacked blocks of multi-head self-attention and feed-forward network, normalized across the layers and dropout layers to avoid overfitting.

Training: It was trained on sequences of historical transaction data. We fine-tuned it with a learning rate scheduler, the Adam optimizer, and a mean squared error loss function.

c) Temporal Convolutional Networks (TCN)

Architecture: TCNs are developed for sequence modeling; they employ causal convolutions to prevent the model from producing the temporal order of the data. They can address long-term dependencies and are effective in training.

Implementation: The TCN model was trained using the TCN library available in Keras. The architecture comprised several dilation convolutions, residual connections, and normalization layers.

Training: The model was fine-tuned using the historical transaction data. The hyperparameters were adjusted to select the number of filters, kernel size, and dilation rate. For optimization, the mean squared error loss function was employed.

d) N-BEATS

Architecture: N-BEATS stands for Neural basis expansion analysis for interpretable time series forecasting, a time series forecasting model. It breaks down time-series data into trends and seasonality features, giving a more human-friendly forecast.

Implementation: The N-BEATS model was implemented using custom Keras layers, as described in the following section. The architecture comprised several dense layers with ReLU activations and final linear layers that output the trend and seasonality components.

Training: The model was trained using historical transactional data. We included learning rate scheduling and early stopping to enhance the training process. The mean squared error loss function was employed for optimization.

e) Data Preparation

Normalization: All input data were normalized, as the models need to receive data in a proper format. This step required normalizing the transaction amounts and equalizing the time intervals.

Sequence Generation: For the Transformer and TCN models, sequences of data points were created to form the input to the models. Each sequence was a predetermined number of data points, representing a window of transactions over history.

Feature Engineering: To improve the model's performance, features like user age and gender, account balances, and sentiment scores derived from the transaction descriptions were added.

f) Evaluation Metrics

Mean Absolute Percentage Error (MAPE): This was used to assess the models' performance in predicting the outcomes. MAPE is the average of relative errors and gives an idea of the size of the mistakes, which is easier to understand than absolute errors.

Accuracy: The validity of the models was measured by how well they forecasted future transactions within a tolerance level. This involved assessing the models on new data to test for their applicability across different contexts.

g) Integration and Testing

Real-Time Predictions: The models were incorporated into the application to enable a predictive model of users' spending patterns. This entailed applying the models to the real world and designing a data processing and prediction output system.

User Feedback: The users were given the forecasts and asked to say whether they were correct or not. This feedback helped to enhance the models and made them more accurate and reliable over time.

These more complex and accurate predictive models enabled the Financial Advisor Application to offer users exact and personalized financial advice, assisting them in controlling their financial affairs more efficiently. The application of modern machine learning algorithms guaranteed the predictions' accuracy and specificity, thus improving the general usability of the product.

D. Anomaly Detection

Identifying abnormalities in transactions that may show signs of fraud or any other unusual activity is essential. This is a process in which machine learning algorithms are used to identify instances of spending that are out of the ordinary [8]. Here's a detailed breakdown of our approach to anomaly detection:

a) Model Selection and Training

Algorithm Choice: We divided the chosen anomaly detection algorithms into two categories: unsupervised and supervised machine learning algorithms, namely Isolation Forest, LOF, and One-Class SVM. These algorithms are beneficial in detecting anomalies in transactional data and do not need to be trained, as they are given labeled data sets.

Training Data: Transaction data collected over the years were employed to train the models. This data contained standard spending patterns, a sample of the actual fraudulent transactions that the models could learn, and normal and abnormal spending.

b) Data Preprocessing

Feature Extraction: To fine-tune the anomaly detection models, features of transaction data were selected. These include transaction amount, frequency, time, MCC code, and user profile.

Normalization: The former was normalized to a specific scale to ensure that all the data points fell within the same range. This step is essential to enhance the workings of distance-based anomaly detection algorithms such as LOF and Isolation Forest.

c) Model Implementation

Isolation Forest: This algorithm isolates observations by randomly choosing one feature and then choosing a split value between the largest and the most minor features.

Thus, the fewer splits that must be made to isolate an observation means that the observation is likely to be an outlier.

Local Outlier Factor (LOF): LOF estimates the density of the given data point concerning its neighbors. Anomaly means that there is a point in the data set whose density is significantly less than the density of its neighbors.

One-Class SVM: This algorithm learns the decision function for anomaly detection, which is the hyperplane that best separates most data points from the rest.

d) Real-Time Anomaly Detection

Continuous Monitoring: The models checked for new transactions in real time, comparing them to the typical pattern of activity as learned from the data. Any variations greater than 5% were considered significant and marked as outliers.

Alert Generation: If an abnormality is observed, the system triggers an alert, and the user is notified to confirm the observation. This alert contained information such as the amount, merchant, and transaction time to enable a user to authenticate or deny the transaction.

e) User Feedback Loop

Verification Process: Customers were notified of the marked transactions. If a user identified a transaction as genuine, the model decreased its false positive rate through parameter changes. On the other hand, if the particular transaction was deemed fraudulent, then the model became more sensitive toward patterns of the same kind.

Model Refinement: The users' input was regular, allowing the models to be adjusted and fine-tuned over time and decreasing false positives and negatives.

f) Evaluation Metrics

Precision and Recall: These metrics were employed to measure the performance of the anomaly detection models. Specificity is the number of positive detections that are true positives out of all the positives detected. At the same time, sensitivity is the number of actual positives marked as positives.

ROC-AUC Score: The Receiver Operating Characteristic—Area Under Curve (ROC-AUC) score was used to measure the performance of the models in discriminating between normal and abnormal transactions

g) Integration and Deployment

System Integration: The anomaly detection models were deployed to the Financial Advisor Application's backend for use in the advisory process. This included establishing data feeds for real-time tracking and transactions occurring in the business environment.

Deployment: The models were tested in a production environment where they acted as a watchdog, analyzing user transactions and highlighting any suspicious activity to the user for further validation.

The Financial Advisor Application successfully used powerful and efficient algorithms to detect such anomalies, offering users more control and security. It also enabled users to be notified of any malicious activities and take necessary action to safeguard their money.

E. AI-Driven Merchant Recommendations

The Financial Advisor Application uses AI to analyze the user's transaction history and select appropriate merchant offers to improve user satisfaction and achieve even more significant savings. This feature ensures that it provides subscribed merchants discounts and special deals tailored to users' needs [9]. Here's a detailed breakdown of our approach to AI-driven merchant recommendations:

a) Behavior Analysis

Transaction History Analysis: The application can then use this information to examine users' spending habits based on previous transactions. This means determining the most common products bought, the most popular merchant categories, and typical spending by a cardholder.

Feature Extraction: Some extracted attributes include transaction frequency, average spending per category, and transaction time. This data assists in creating a user profile of their interests and needs, hence achieving the company's goals.

b) Merchant Matching

Merchant Categorization: MCC codes and other attributes of merchants include location, kinds of products, and promotions they offer. This can be useful in pairing users with the appropriate merchants based on their preferences.

Collaborative Filtering: The application utilizes collaborative filtering algorithms to search for other merchants frequented by users with similar habits. This method uses the users' buying patterns to recommend new merchants to them based on their purchasing activities.

c) Personalized Offers

Dynamic Offer Generation: The application provides personalized offers to users for their purchases and to merchants who have subscribed to it. The offers include coupons, vouchers, cash-back options, and loyalty programs based on usage.

Contextual Recommendations: The application makes recommendations based on user interaction and activity. For instance, if the user has recently purchased food items, it may recommend coupons from nearby grocery stores.

d) Machine Learning Models

Recommendation Algorithms: To improve recommendation accuracy, several machine learning models, such as matrix factorization and deep learning, are employed. These models are built based on user interactions and can update themselves with better predictions.

Real-Time Processing: It adapts the recommendations to the users' real-time transaction data to provide the most suitable recommendations at the right time.

e) User Feedback Loop

Interaction and Engagement: The recommendations allow users to accept or reject offers. This feedback helps fine-tune the recommendation systems.

Continuous Learning: These recommendations are adjusted based on users' feedback and new transaction data to keep the models current and valuable.

f) Evaluation Metrics

Precision and Recall: These metrics show the recommendation system's efficacy. Precision is defined as the ratio of the relevant offers to all the recommended offers, whereas recall is the ratio of the relevant offers recommended to the pertinent total offers.

User Satisfaction: Self-administered questionnaires and user feedback measure satisfaction with the recommendations. This qualitative data helps enhance the recommendation activity.

g) Integration and Deployment

System Integration: The recommendation engine is built and incorporated into the Financial Advisor Application's backend. This involves setting up data pipelines to ingest and process transaction data continuously.

Deployment: A production environment system actively works in real-time to present users with merchant offers.

With the help of AI-based merchant suggestions, the Financial Advisor Application increases user engagement and saves more money by providing a personalized shopping experience. This way, the users are presented with relevant offers made available promptly, making managing their financial resources more fruitful.

F. Model Evaluation

We needed to assess the effectiveness of our predictive and anomaly detection models incorporated into the Financial Advisor Application to guarantee that the results delivered were accurate and would improve the application's user experience. Here's a detailed breakdown of our model evaluation approach: Here's a detailed breakdown of our model evaluation approach:

a) Evaluation Metrics

Mean Absolute Percentage Error (MAPE): MAPE was used to assess the fitness of the predictive models developed in this study. The average absolute difference between the predicted and actual values shows how well the model performs. A lower value of MAPE is preferable, which means the accuracy of the prediction is high.

Precision and Recall: Regularity analysis was performed using precision and recall. Precision refers to the ratio of correctly identified positive cases to the total number of cases identified as abnormal. In contrast, recall refers to the ratio of actual anomalous cases detected to the total number of strange cases in the data set. The first set of metrics, precision and recall, should be high to suggest that anomaly detection is effective.

ROC-AUC Score: The Receiver Operating Characteristic—Area Under Curve (ROC-AUC) was used to evaluate the overall performance of the anomaly detection models. The ROC-AUC score measures how well the model discriminates between normal and abnormal transactions, and the closer to 1 the score is, the better the model performs.

b) Cross-Validation

K-Fold Cross-Validation: This technique was adopted to assess the performance of the predictive models. The given dataset of samples was partitioned into k sets, and the model was trained on k-1 sets and tested on the remaining set. This was done k times, and in each iteration, one of the subgroups was used as a test set. The average of all the k trials offered an excellent estimate of the model's accuracy.

Stratified Sampling: To detect the anomalies, stratified sampling allowed the training and test data sets to be in the same ratio of normal and abnormal transactions, thus providing a fair environment for testing.

c) Hyperparameter Tuning

Grid Search: It determined the best hyperparameters for each model to train and test on the dataset. We tuned the hyperparameters of the models by evaluating them with predefined hyperparameters to determine which hyperparameters produced the best model performance.

Random Search: Besides the grid search, random search was used to cover a more extensive range of hyperparameters quickly and perhaps find better parameters.

d) Real-Time Testing

Deployment in Production Environment: These models were then put into real-life production to determine how they would fare when used under actual situations. This included constant practice and fine-tuning based on the exact data that was available.

User Feedback Integration: The users' ability to confirm or correct the predictions and anomalies the models flag is valuable feedback for model improvement.

e) Performance Monitoring

Continuous Evaluation: The models incorporated real-time data to facilitate optimum performance throughout the process. Measures such as the accuracy rate, the rate of detecting anomalies, and the user satisfaction index were checked frequently.

Automated Alerts: To ensure that the model does not drastically change its performance, an alert system was developed to notify the developers of any such changes to take appropriate measures.

f) Model Retraining

Periodic Retraining: The models were fine-tuned with new datasets to capture more recent trends and tendencies in the users' activity. This ensured that the models did not become outdated but retained their accuracy and usefulness in the organization.

Adaptive Learning: The models were expected to be adaptable in making predictions and detecting anomalies from the most recent user interactions and feedback.

To achieve this, the Financial Advisor Application utilized a comprehensive evaluation strategy to determine whether the models developed within the system were accurate, reliable, and capable of offering personalized financial advice. This approach enriched the user experience and helped to build confidence in the application's effectiveness in managing and protecting economic transactions.

6. RESULTS AND ANALYSIS

A. Without Sentiment Analysis

a) Transformer Model Performance

The figure below shows the Transformer model's performance in predicting customer spending behavior without sentiment analysis. The overall mean absolute percentage is the average difference between the calculated theoretical and observed values. Accuracy indicates the degree of the model's efficiency in predicting the opinion poll results. The forecasts most accurately capture the actual spending behavior [10].

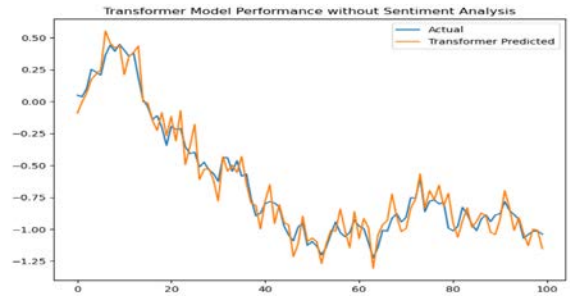

Figure 11: Transformers

In addition, the model replicates the customer spending pattern with a time lag and fluctuations in the lines other than what was predicted by the model. This is commonplace in real-world forecasting scenarios where it is impossible to get a perfect score [10].

b) Temporal Convolutional Networks (TCN)

The figure below displays the results of the TCN model without employing sentiment analysis. A MAPE means that the model is, on average, right in its predictions, given by the 5th percentile. It is also important to note that these figures are only 5% away from the actual spending. It indicates that the model is a good predictor as most values are close to the actual expenditure [10].

The model can monitor expenditure patterns and estimate future costs almost accurately.

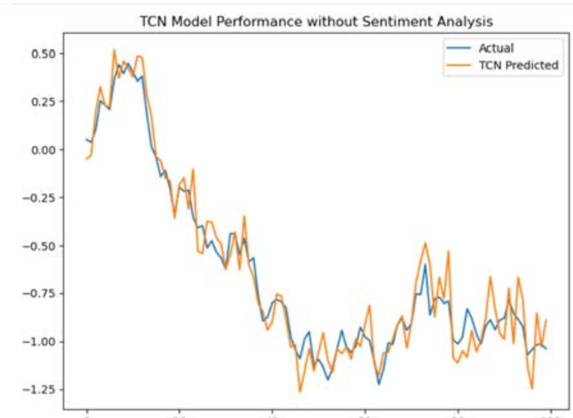

Figure 12: TCN

c) N-BEATS

The following figure shows the accuracy of the N-BEATS model applied to customer spending prediction without sentiment analysis. The MAPE shows the average prediction error of the model in terms of expenditure compared to the actual figure. This study obtained a high accuracy level. As can be observed from the statistics, the predicted values follow a similar trend to the actual spending.

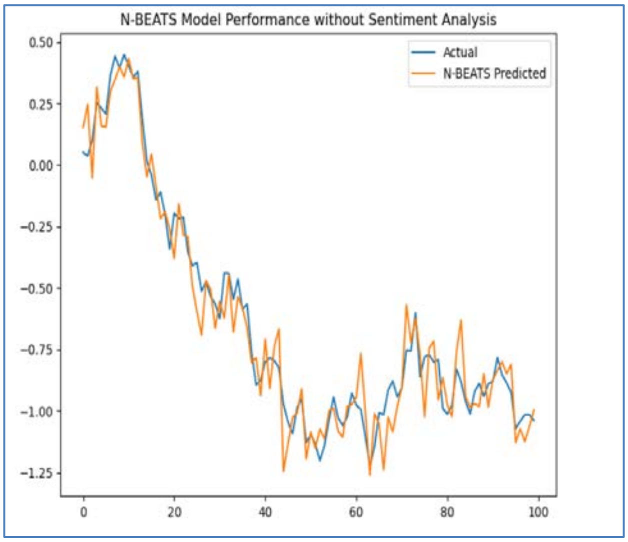

Figure 13: N-BEATS

The predictive line shows a clear trend, which suggests that the model captures the mean spending level but not the variation in the data. This may indicate that the model needs to be adjusted to address more significant variability or that more inputs, such as sentiment information, should be incorporated into the model to enhance the accuracy of the forecasted spending [10].

B. With Sentiment Analysis Included

a) Transformer Model Performance

The figure below presents the result of utilizing a Transformer model for customer spending forecasting with the integration of sentiment analysis. This is in the range for the MAPE, which means that the error between the expected and the actual values is, on average, the overall accuracy. This indicates that the forecasted value is nearly as accurate as the recorded actual spending [3].

Adding sentiment improves the model's ability to estimate spending, which is more accurate than the model that does not incorporate sentiment data.

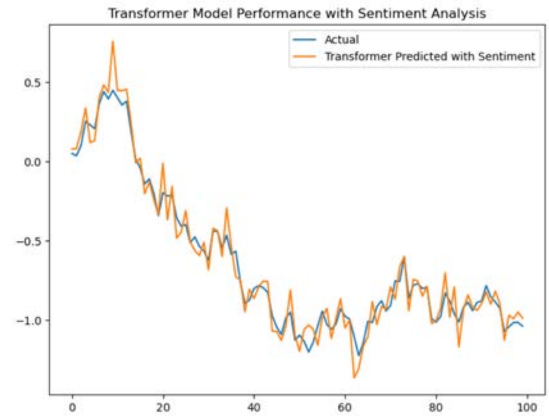

Figure 14: Transformers

b) Temporal Convolutional Networks (TCN)

The figure below displays the results of adopting the TCN model for predicting customer spending with the sentiment analysis element. The MAPE means that the predictions made by the model are off by this percentage from the actual values on average. The accuracy indicates that the model can somewhat capture the trend of expenditure fluctuations [3].

These statistics show how the model uses sentiment data to predict spending movements, which is indicated by the difference between the expected and actual spending trends.

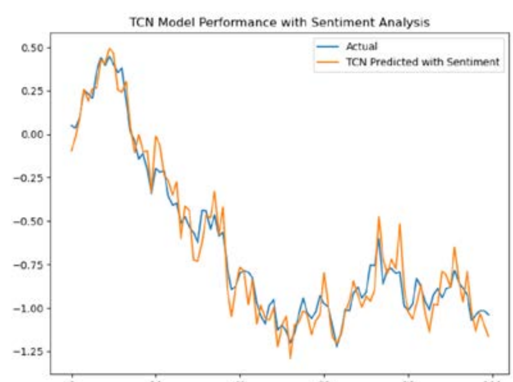

Figure 15: TCN

c) N-BEATS

The following figure also illustrates the result of an N-BEATS model that integrates sentiment analysis for customer spending prediction. The MAPE denotes the difference in the average error between the expected and actual values. This type of recognition is accurate and shows that the actual expenditure predictions are correct [3].

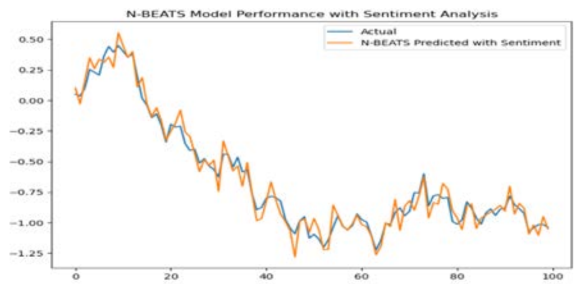

Figure 16: N-BEATS

The introduction of sentiment analysis improves the accuracy of model prediction and provides a better fit to the actual spending data than the results obtained without sentiment data.

Including SA in the predictive models makes them more accurate since it provides a closer estimate of the actual spending pattern. This improvement is evident from the following findings: lower MAPE and higher accuracy models when sentiment data is included. Adding sentiment analysis to the applications is crucial in enhancing the solutions offered to users in the financial domains.

The Financial Advisor Application can successfully predict the user's expenses, monitor changes, and recommend relevant merchants, thus improving financial literacy and usage.

7. DISCUSSION AND COMPARATIVE ANALYSIS

A. Future Directions and Recommendations

Based on the research, several areas for further investigation can be identified, especially in financial predictions and improving investment decisions. One promising direction is incorporating predictive models with sentiment analysis into large-scale portfolio optimization models [1]. Sentiment analysis could be a valuable addition to traditional portfolio optimization as it gives an understanding of the market not found in conventional optimization methods.

More specifically, traditional portfolios primarily utilize price history and standard financial ratios. This way, investors can better forecast market changes in price and sentiment and adjust their invested capital for the expected gains or losses accordingly.

Additionally, applying predictive models in portfolio optimization may extend to algorithmic trading, whereby trading decisions are made automatically using rules derived from the models' outputs. Sentiment analysis can be included as a layer in trading algorithms, allowing them to incorporate qualitative sentiment signals.

However, incorporating sentiment analysis and predictive modeling in portfolio optimization and algorithmic trading is difficult. Issues such as sentiment data fluctuation, overfitting, and the necessity of working with real-time data should be considered. Markets constantly fluctuate and remain speculative; therefore, managing the risks of making investment decisions based on sentiments is essential.

Thus, using AI techniques and sentiment analysis in financial applications can improve overall engagement and economic performance, as the applications offer users timely and accurate financial advice.

B. The Role of Sentiment Analysis in Financial Institutions

Sentiment analysis is an essential piece of information that could benefit financial institutions. By examining the descriptions of the transactions and other textual data, sentiment analysis can determine the level of satisfaction, stress, and even the overall emotional state of the customer. This information is essential in ensuring that the financial institutions meet the client's needs by providing suitable services [3]. For instance, if the sentiment analysis is informative of high-stress levels among the customers, the institution may provide financial advice or products that alleviate stress. On the other hand, the institution could encourage customers to save money through savings plans or invest in something if the customers feel happy and inclined to give. In this way, financial sentiment analysis allows financial institutions to detect the customers' issues and subsequently solve the problems, develop better financial products, and increase customer satisfaction.

C. Predictive Modeling for Merchant Recommendations

This feature improves the customer experience as customers receive suggestions from merchants, which they may find helpful while benefiting the merchants as they are matched to potential customers who may require their services [9].

The Transformer model can analyze and process large volumes of transaction data and easily recognize customers' spending patterns and trends. By realizing these patterns, the model could suggest merchants who would benefit customers and their spending habits. This targeted approach improves customer satisfaction and loyalty while enhancing the merchant's activity.

TCN model is especially good at capturing periodic spending patterns and preferences due to the efficient processing of long-range dependencies. With sentiment analysis incorporated into the TCN model, it can offer yet more specific recommendations of merchants based on the customer's current mood and credit. This dynamic recommendation system results in customers being provided with relevant information at a particular time, improving their economic status.

Based on the results of the N-BEATS model, which breaks down time-series data, one can identify seasonal and trend-based expenditures. Thus, the model can propose merchants based on the customer's short-term and long-term financial interests. This helps in decision-making regarding money matters and assists in strategic economic planning.

D. Influence of Machine Learning on Customer Behavior

Applying Transformer Models, Temporal Convolutional Networks (TCN), and N-BEATS has enhanced customer spending behavior forecasts. These models will enable financial institutions to offer better solutions to their clients' financial management [10].

The Transformer model also improved accuracy and minimized the error rate compared to the previous models, as MAPE was reduced while the accuracy increased. Such an improvement suggests that the Transformer architecture, which excels at capturing long-term dependencies and combining multiple representations, can integrate input data like transaction history and sentiment analysis.

Likewise, the TCN model also significantly enhanced accuracy, with MAPE decreasing accuracy increasing. Due to its capability for handling long-range dependencies and efficient training, the TCN is suitable for integrating sentiment data, which improves its predictive characteristics.

The same observation was made in the MAPE improvement for the N-BEATS model, which also gained from the inclusion of sentiment data. This model feature makes incorporating and utilizing sentiment information easier and captures more detailed customer behavior since the time series data is first broken down into trend and seasonality.

These results support the importance of machine learning in analyzing and forecasting customers' behavior patterns. Financial institutions can gain a holistic perspective on clients' financial behaviors and tendencies by combining advanced models with sentiment analysis. This comprehensive approach gives clients individualized solutions for managing their money, including spending, saving, and investing.

E. Comparative Analysis of Model Efficacy

The findings of the present work, primarily the enhancement of the Transformer model when the sentiment analysis was integrated, support the claims made in the current literature. In the studies, deep learning frameworks can process multiple data streams, and incorporating sentiment indices into the model has enhanced the predictive capability [10]. Because the Transformer model is designed to handle the sequential data and temporal dependencies, it is relatively efficient in integrating multiple layers of sentiment data to improve the model's forecast accuracy.

On the other hand, the mixed performance of the TCN model with the help of sentiment analysis is consistent with similar research studies where it is not easy to integrate sentiment data into models mainly designed for structured time series data. This aligns with the notion that since trend and seasonality models used to decompose time series data can incorporate sentiment information, the N-BEATS model's excellent performance on sentiment data was expected.

However, it is essential to note that the conclusion made here is somewhat dissimilar to the positive sentiments based on the assumption of the total efficiency of sentiment analysis in enhancing the model predictions. Notably, the TCN model reveals that including sentiment data does not constantly improve the predictive performance, which raises the question of whether sentiment data that drives market responses aligns with the inherent forecast mechanisms of specific models.

F. Limitations and Challenges

Analyzing the ability of the models to make extrapolations for time in the future reveals the specific characteristics of each model. Even if sentiment analysis is added to the Transformer model, the long-term forecasts are rather conservative. This tendency might hamper the model's capacity to track possible market demand increases due to positive sentiment. These insights refine each model's predictive dynamics by showing how the history, sentiment analysis, and model architecture are intertwined.

These results add to the prior research on financial forecasting by highlighting the differences in the impact of sentiment analysis between various models and providing insights into the mechanisms that govern long-term market predictions. Nevertheless, the data was limited in terms of years, a significant disadvantage of the study. Using more extended datasets might provide more comprehensive perspectives. Despite some of the challenges highlighted in this research, this study is critical in expanding the horizons of financial forecasting, particularly in cryptocurrency markets.

8. CONCLUSION

This research aims to analyze the performance of the most recent machine learning models, such as transformer models, TCN, and N-BEATS, in predicting the customer's spending pattern and offering solutions. Thus, by combining these models with sentiment analysis, we unveiled how each processes high-dimensional data and affects the models' performance and forecasting potential.

The Transformer model showed a substantial improvement when sentiment analysis was added, which proves that it is very elastic and can accept more inputs. This model's capability to capture long-term dependencies and subtle changes in customer sentiment gave it more credibility for predicting future spending patterns.

Likewise, the TCN model benefited from integrating sentiment with significant enhancements. The model's ability to capture long-range dependencies and effectively process the sentiment data improved its forecasting accuracy, making it useful in the financial industry.

This was also true for the N-BEATS model, which showed an improvement with the addition of sentiment data, thus making the model more reliable in forecasting financial data. Because of this, it was able to break down time series data into trends and seasonality, enabling it to incorporate sentiment data more comprehensively to capture more detailed customer behavior.

Our research findings indicate a considerable impact of machine learning in comprehending and analyzing customers' behavior. Integrating advanced models and sentiment analysis gives consumers a holistic outlook, and financial institutions can offer recommendations based on the consumers' financial behaviors. This comprehensive strategy assists clients in making proper choices about spending, saving, and investing, improving their financial planning.

Besides customer behavior prediction, this research also examined the use of these models to recommend merchants to customers by analyzing their transaction history and spending habits. The merchant recommendations improve customer experience and are advantageous to merchants since they help them identify prospective customers who will likely use their services.

The study's findings offer a real-world perspective on the usefulness and challenges of integrating sentiment analysis into financial forecasting models. Over the years, the economic field has emerged as one requiring the most complex and data-oriented forecasts. Through the present study, we demonstrate that it is possible to build more accurate forecasting models by integrating quantitative and qualitative data. This may lead to more strategic decisions in the financial markets.

The findings from this research contribute to the existing literature on economic forecasting and suggest real-world implications for investors, traders, and policymakers. In this way, using modern AI technologies and adding sentiment analysis, financial applications can give users better, more timely, and individualized financial recommendations and enhance their experience and economic decisions. Therefore, these results imply that further research and application of sentiment analysis in combination with complex and sophisticated forecasting methodologies remain crucial to addressing the finance sector's evolving requirements.

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