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Transforming Personal Finance Coaching through Artificial Intelligence

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Abstract

Artificial intelligence (AI) has bloomed in recent years and is gradually becoming an irreplaceable asset in finance, among other sectors. Personal finance is a subset of finance, which too is being revolutionized due to changing times and technological advancements, much like AI. Security and proper financial guidance have never been more important with such significant change. In this study, we use FinBERT, a modern large language model specialized in the financial domain, for our AI-powered personal finance coach. However, FinBERT, although a cut above the rest, still has room for growth, so we aim to improve its flaws and enhance its efficiency. We established that FinBERT succeeded in detecting sentiments in explicit sentiments, but was not usually successful in doing so correctly for implicit sentiments. FinBERT, despite its limitations, has a high accuracy and is the best model to use in our study. This model can also be utilised to provide accurate results regarding the overall trend (positive or negative) of the global stock market. Our results demonstrate that integrating AI in personal finances is feasible and can successfully aid individuals in making decisions regarding their finances.

Keywords: FinBERT, AI, Personalized Financial Coaching, BERT, FinTech

1. Introduction

In this digital era, technology and financial procedures are much more advanced than they were, a decade ago. New technologies including cloud computing have emerged ever since the Industrial Revolution. One of these is Artificial Intelligence (AI), which has already begun to fundamentally impact how we use data and machines [1]. Artificial Intelligence refers to creating computer systems that are able to do tasks that require some degree of human intelligence, whether that be solving problems, making decisions or simply learning. Its applications in the personal finance industry can be seen in banks, insurance companies and others [2,3]. One could argue that AI truly emerged in the early 1950s when Alan Turing, also known as the 'Father of AI', published his paper, "Computing Machinery and Intelligence", where he discussed the creation of intelligent machines and ways to test their intelligence [4]. Five years after he published his paper, his concept took physical form, as the 'Logic Theorist'. It was a program developed by Allen Newell, Cliff Shaw, and Herbert Simon, and funded by the Research and Development Corporation (RAND), which could mimic the thought process of a human [5].

AI plays an important role in many aspects of society from self-driving cars, and video games to digital assistants like Apple's Siri [6,7]. Additionally, it has a positive effect on the world economy, as Russia has a GDP of $2.24 Trillion and the United States has a GDP of $25.44 Trillion in 2022 [8]. This staggering rise can be explained by improved financial means like cost-saving patterns, and prevention of threats - physical and digital, along with other factors. Some of the world's largest tech companies like Amazon, Google, and Facebook are investing vast amounts of money into AI, specifically digital assistants [9]. As customers and clients switch to digital platforms, traditional companies are also switching to keep up with the tide, becoming more customer-centered [10]. According to Forbes, in 2022, 78% of adults residing in the US preferred to bank through an app or website while only 29% preferred to do so in person [11].

And in the light of these groundbreaking advancements, our research aims to use AI models to improve upon the financial procedures we have right now, such as credit analysis, financial planning, evaluating investments, etc. and enhance financial coaching [12]. FinTech companies play a huge role in this, as many companies in the sector develop AI tools that specialize in the field of finance [13]. Amongst the models that FinTech companies have created, FinBERT (Financial sentiment analysis with Bidirectional Encoder Representations from Transformers) is one of the most influential models they have made because of its accuracy in its findings [14]. FinBERT is a pre-trained AI model that has been used in the financial world for testing. It is pre-trained on specific words and expressions to help out in any field. It is mainly used in finance as a robot chatbot or a robot financial advisor at a firm. FinBERT is based on BERT from Google. BERT can be used in many different fields, but FinTech based FinBERT on BERT's algorithm procedure, specifically, the pre-training portion [15]. Our study's objective is to use FinBERT particularly, as a financial AI coach to keep up with the evolving personal finance industry. AI in finance is a growing idea that has long been a dream for many people, but multiple companies like FinTech are trying to make that a reality.

2. Methods

2.1 Introduction to AI-Powered Personal Finance Coaching

Coaching is an essential concept, which caters to all kinds of people with different reasons for acquiring guidance, whether it be a more balanced lifestyle or a simple break. Successful coaching outcomes are strongly linked to the relationship between the client and the coach [16,17]. The current traditional technologies, including Automated Teller Machines (ATM) or accounting softwares like QuickBooks, have proved to be insufficient for the evolving field of personal finance. And, as mentioned before, AI has already begun to impact the industry through algorithmic trading, virtual customer assistants, market analysis, and other techniques [18]. Studies suggest that although in coaching, AI may lack emotional depth and the working of a human mind that is required in coaching, it can still be considered a feasible option for providing support. An example is an AI agent utilizing cognitive behavioral therapy (CBT) which successfully alleviated symptoms of depression and anxiety in college students [19]. Moreover, it is crucial to have an AI personal finance coach to expand the scope and aid individuals worldwide in accessing financial guidance. This could lead to significantly reduced costs, and behavioral biases, increased profitability, forecasts in financial markets and the execution of algorithmic trades amongst many other applications [20,21].

2.2 Data Collection and Preprocessing for Financial Coaching

For years, even decades, the data collection and management for investment funds and financial consulting have all been done by hand. It takes too long and there is a guaranteed chance of having some errors in it. However, according to fintech, AI can do this significantly faster [22]. Robo-advisors are coming into play now and they are taking the spotlight. They can exist through online investment platforms or brokerage concerning only two things: customer assessment and portfolio management [23]. The portfolio management is the most important part of investment platforms as that is what holds all your financial information. AI has top notch security in sending and receiving data since it is trained specifically for that job. AI takes that data earned from the client and then sends it straight to the portfolio instead of a human sending it to someone else via cloud and then that person sends it to the portfolio. AI can be trained to have a model that sends data with the utmost privacy and security. Because of this, the AI models are trained using special APIs designed specifically for those instructions [24].

The way AI obtains its data can be used in any field, it doesn't have to be in finance. A key example of that is the COMET study from Stanford University. These researchers developed an electronic network infrastructure to collect and link prospective data from multiple clinical centers and multiple patients [25]. This system they made uses the same data collection technique as AI and other finance advisors do, but sets it on a different scale. Instead of just looking through the dataset of one person, this network looks through a group of people at different hospitals at the same time [26]. Since it is AI, it can be trained to do the data collection processes in any environment and it can even make the data cleaner by shaving off the extra bits. AI takes the data through multiple cleansing processes that cut the data down to its bare bones so it can be seen in its raw state with the most important information and that only. Not only that, but it fixes the imperfections as well. Data is available publicly about current and past financial markets and economic indicators for markets, so this would be easy to acquire and use to train an AI model. Data collections for Fin BERT is one of the most important parts to think about while training it. Finance models should have good privacy while still being able to have fast computing, so the data collection process is a big part. Because of that, this process tends to have a lot of problems depending from model to model, so the fact that Fin BERT hasn't had nearly as many problems is big plus to everything else about it.

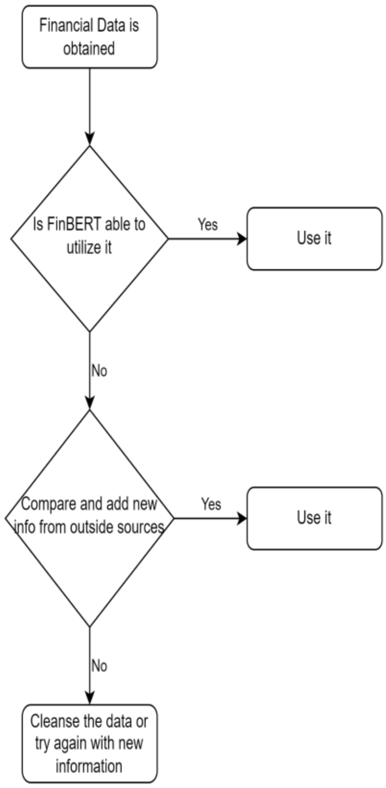

Figure 1. An overview of the FinBERT data acquisition and financial data fix

2.3 AI Model Architecture for Personal Finance Coaching

FinBERT, also known as BERT (Bidirectional Encoder Representations from Transformer) for Financial Text Mining, is a pre-trained Natural Language Processing (NLP) model based on the standard BERT architecture, designed specifically for the financial domain [27]. It uses a transformer-based architecture, similar to that of BERT, and follows the two-stage pre-training language model (Pre-training and then Fine-tuning) approach which has started gaining popularity in NLP. The FinBERT model differs from BERT in the methods of pre-training. BERT uses MaskLM (Masked Language Modeling), which means inputting missing words based on the context and

NSP (Next Sentence Prediction), which helps to grasp the relationship and relevance between sentences [28]. While FinBERT uses a plethora of different pre-training objectives to better obtain language knowledge and connotation information. FinBERT also continuously keeps updating the pre-trained model through multi-task self-supervised pre-training learning. It is simultaneously trained on a general and financial collection. FinBERT is first formatted with the pre-trained guidelines during fine-tuning, and then later fine-tuned on the task-specific managed data [29].

Fine-tuning the whole model requires extensive time and computing power. Studies show that fine-tuning only the last layer of the model is enough to surpass advanced machine learning methods like HSC (Hyper Suprime-Cam) [30]. FinBERT has a multi-layer Transformer encoder with a self-attention mechanism to capture global context information through pairwise correlation. In other words, it is using the relationships between pairs of components to build a comprehensive understanding of the whole. As for the pre-training data, we used data from the English Wikipedia and Books Corpus, which were also used for BERT [31]. These have a total of 5.5 billion words. We also used Reddit Finance QA (question-answer pairs about financial problems with at least 8 upvotes), Yahoo Finance (filtered financial articles with only relevant information) and Financial Web (filtered news from the last 25 years).

This model architecture may present certain challenges. One such issue is class imbalance, where the frequency of instances in one class significantly surpasses that of others. This imbalance can skew results and introduce bias into the model. Addressing class imbalance involves either augmenting the instances of underrepresented classes, reducing the instances of overrepresented ones, adjusting the class weights within the system or even using an ensemble-based method (biased random forest) [32]. Additionally, the pervasive 'black box' problem presents another challenge. This issue, characterized by the obscurity of AI decision-making processes, undermines trust between the AI and its users and raises ethical concerns about potential biases. Solutions include employing feature importance techniques, which highlight the variables most influential on the model's outputs, and designing the model to explain its decisions, rather than retrofitting explanations post-development [33]. Though many challenges could arise, there are also many solutions that can be implemented to counteract them.

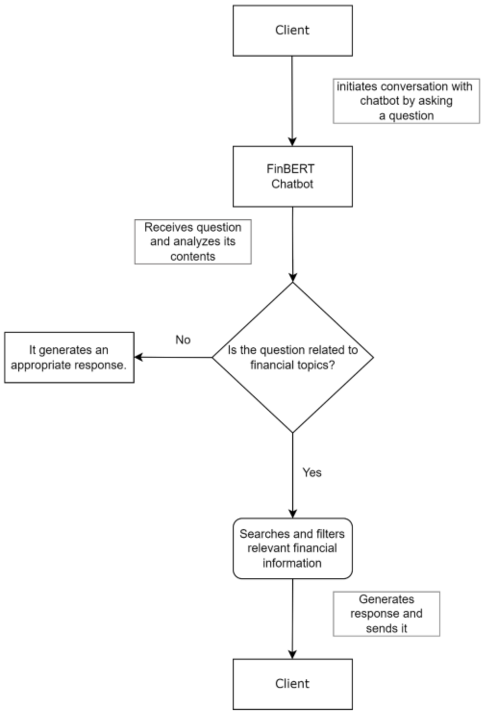

Figure 2. An overview of how our AI chatbot works.

2.4 Evaluation Metrics and Benchmarking

Evaluating the effectiveness of a personalized AI finance coach and comparing it to a human financial advisor can be difficult, but with the right methods, it can be done. There are many different ways to compare AI coaching to human coaching as well as seeing which one is the superior option for learning in the world of personal finance. Some of these methods are checking if the clients' goals align with the SMART template, diagnosing a client's financial problem, and considering the consequences and potential ramifications of going through with a potential solution [34].

When checking whether the goals presented by FinBERT align with the SMART values (Specific, Measurable, Achievable, Relevant, and Time-Bound), AI coaching is reliable and asks its clients about how their goals can relate to SMART goals. However, it does not have much tolerance for error much like a human financial advisor. It cannot find mistakes in the prompts that it gets and doesn't ask the user more about what they want [35]. When approached with the question of identifying a problem with a client's finances, AI makes them reflect on their actions that led up to the problem and provides feedback to solve the error so it doesn't happen again. However, it reads between the lines and doesn't ask about the client's intention with their actions and does not explain how it diagnosed the issue and made a decision [36].

Finally, when asked about the effects of the decisions it suggests clients to make, it generates a list of positive and negative consequences for the list of solutions that it makes and allows the client to provide feedback on its solutions to improve on its future helpfulness with providing a solution [37]. Overall, an AI-powered finance coach can help clients significantly by providing detailed and clear feedback, diagnosing an issue with the clients' finances, asking about their thoughts and ideas along with navigating through the task of setting goals and helping achieve them. It still lacks in a lot of areas compared to actual financial advisors and is nowhere near as detailed, but it can help generate foundational thoughts and ideas for the client to use.

2.5 Ethical Considerations in AI-Driven Financial Advice

Creating an AI personalized finance coach requires a massive amount of customer data. Due to this, there are several ethical concerns which should be considered when creating such a model. One of the biggest concerns is AI bias. Historical data that is used to train AI can contain biases towards certain groups, potentially resulting in a model that unfairly favors or discriminates against individuals in those specific groups. This bias could lead to flawed financial advice for some users, adversely affecting their financial health. Bias in the AI model could be diminished by continuously monitoring for fairness, and by identifying processes where bias is present and eliminating it. These processes include Style Transfer Data Augmentation, Targeted Data Augmentations (general and targeted), and Attribution Feedback.

Data privacy and security is also a concern. When an immense quantity of data is used, a primary issue is whether or not data is used for the intended purpose only, or for other, possibly malicious, purposes unbeknownst to customers, as well as the security of data. Developers must use strong security systems to protect data and obtain consent from users before using their data to train AI models to be ethical when creating models. They must also comply with regulations enforced by governments regarding data privacy and security. Another concern is unemployment. If a successful working model is developed, it might initially result in job losses as the model supplants human roles. However, over time, it could generate new employment opportunities in various fields and enhance the accessibility and convenience of personalized finance coaching for people, especially individuals who cannot currently afford personalized coaching. That said, the people who will be replaced by AI will still struggle to find a job in the same field and will suffer. To address ethical concerns, developers can deploy ethical frameworks when implementing AI models, adhere to ethical guidelines set by authorities, and establish feedback platforms for users [38, 39]. While there are numerous ethical considerations regarding the use of AI in financial coaching, many of these concerns can be effectively resolved or mitigated with efforts from developers. On the other hand, some ethical issues such as potential unemployment may be difficult to counter.

2.6 Limitations and Future Directions

AI in finance has been at the center of attention for decades, with both classic and modern AI techniques applied to areas of finance, economy, and society, with some of these specific areas including financial markets, trading, banking, insurance, risk, regulation and marketing, with the goal of making them more efficient. However, these innovations also come with an overwhelming number of challenges [40]. Primarily, there are challenges that financial businesses experience when implementing certain AI techniques, some of these including; hardships in data quality, data availability, complex dependencies, and non-stationarity. Firstly, problems in data quality are experienced as it is necessary to provide high-quality data for accurate AI models, but financial data could be noisy, incomplete, or inconsistent. Some mitigation strategies for combating these issues with data quality would be data cleaning and preprocessing; where techniques like outlier detection, imputation, and normalization can enhance data quality by changing it to be usable for AI models [41]. Additionally, creating relevant features from raw data could improve model performance in regard to its challenges with data quality. Secondly, this performance could potentially be limited due to privacy concerns or data registered under trade names, can be solved for the future if financial institutions can collaborate to share non-sensitive data while also respecting privacy regulations. Lastly, financial systems exhibit complex inter-dependencies, making modeling and prediction of data challenging, and financial data also often violates the assumption of requiring adaptive models. Some mitigation strategies for this include the making of graph-based models which represent financial systems as graphs to capture complex dependencies, and this allows graph neural networks to learn from these structures as well.

Also, there are many challenges involved in the physical data itself, other than issues with data quality. These challenges include heterogeneity, the diversity and variability of data sources within stock market datasets, seen as data from various sources, differ significantly. Some examples of these various sources would include the usage data from stock markets, credit scores, or economic indicators. This challenge could be combated with data standardization, where this diverse data would be converted to a standard form and common data models will also be used to align these different data sources. Advanced technologies could also be used to combat this challenge of heterogeneity, one example being using machine learning models to detect patterns and standardize data across heterogeneous sources. Similarly, other data challenges also include time dependencies and trends, where feature selection and dimensionality reduction could be made critical if the data had many features, and model performance could get heavily impacted due to imbalances between classes [42]. Some mitigation strategies to overcome these issues of time dependencies, trends, feature selection, dimensionality reduction, and class imbalances are feature engineering, embedded methods, autoencoders, resampling methods, and some general strategies such as data augmentation. Feature engineering is where features that capture temporal information, such as time laga, rolling averages, and trend indicators, will be created, so as to combat the issue of feature selection. Feature selection techniques such as embedded methods use algorithms that perform feature selection during the model training process, and this too will address issues with feature selection. Next, autoencoders solve issues with dimensionality reduction by using neural networks to learn compressed representation of some data. Lastly, resampling methods such as under sampling will handle class imbalances by reducing the number of instances in the majority class of the data set, and some other general strategies such as data augmentation will also work to improve model performance by creating synthetic data to augment the training set, which can help in addressing both class imbalances and temporal trends.

Overall, despite the many challenges from AI in finance, understanding the historical context of both classic and modern AI techniques that are applied to financial domains helps address these current challenges, as these modern techniques have evolved based on classic methods and this knowledge will also help us create more effective models. Furthermore, by studying these classic AI techniques, like statistical models, we gain some insights into their strengths and limitations while also providing a base for understanding the evolution of AI in this sector [43].

3. Results

In the personal finance industry, traditional investment options often involve consulting with a bank and sticking to standardized investment plans. These plans typically offer a limited number of stock options and have a significant risk factor in terms of the returns. However, an emerging alternative to this traditional way uses the help of artificial intelligence and goes down the path of using personalized AI chatbots. These chatbots are customized to provide tailored investment advice and support, with minimal fees or commission, to educate about a broader number of investment plans that may be overlooked or not mentioned in the traditional consulting's. And one of these AI bots is FinBERT, a sentiment analyser. Feeding a sentence into the bot can return a positive, negative, or a neutral value. This can make investing a lot easier by feeding financial articles or headlines for newspapers of a particular stock. Utilizing the sentiment values of the public can guide one to create a smarter and high performing stock portfolio.

With a couple of tests on the pre-trained FinBERT model publicly available, we received mostly positive results overall with the accuracy and usefulness of the AI model, with a 66% correlation rate between stock movements and results from FinBERT along with 91.3% accuracy when completing tests. After finding general financial articles about the current stock market, we fed text from those articles into the model.

However, with some newspaper headlines that were passed that seemed positive, the AI interpreted it as neutral or negative. These headlines essentially conveyed positive sentiments, yet the AI required explicit lingual indicators to accurately interpret them. This limitation is one of the many challenges associated with FinBERT; its inability to distinguish emotional direction in the absence of explicit keywords, and this limitation constrains its capacity to provide accurate advice, restricting the scope of its recommendations. This finding was unexpected, particularly given that FinBERT was trained on a collection of approximately 5.5 billion words, which should have enabled it to better understand and infer underlying and implied market sentiments [44, 45].

FinBERT had the highest accuracy and precision at 91.3% compared to its competitors NativeBayes at 67.8% and BERT at 88.2%. This means that it is reliable in guessing the sentiment of the articles fed to it, even if it cannot read implicit ideas in a sample. This can be useful in guessing investor sentiment in a particular stock, and detecting the movement and with how good of a purchase you are making. With a 66% correlation (Pearson's correlation coefficient of 0.6613) between consumer sentiment and stock prices, there is a strong relationship suggesting that if there is a higher consumer sentiment, then the stock price will also move up. This is a strong correlation, especially since the AI model can be used to predict a stock's sentiment positively and will most likely cause stock prices to increase. This is good news for the future of personal finance coaching because FinBERT is a publicly available AI model, and can be used by anyone for free [46].

4. Discussion

The personal finance industry is growing and attracting the attention of many individuals from diverse backgrounds, who require its services. AI plays a huge role in making these services accessible to more people. Numerous studies indicate that AI can imitate human financial advisors and offer tailored effective financial advice, expanding its reach. This study focused on an existing NLP finance model, FinBERT, and aimed to improve it further, explaining the reasoning behind the selected features used in the model. By doing so, we hope to shed more light on financial bots' capabilities and improve the relationship between these bots and clients. While FinBERT can work effectively in English, due to its large corpus of financial and general text, it is unable to do so with other languages. This is due to the limited overall text available in foreign languages, which hinders the model's performance, making it not as accurate in comparison [47].

The complex and highly trained financial sentiment model FinBERT is considered reliable and efficient compared to similar financial AI models. However, there are cases where it cannot adequately predict the positive or negative nature of a particular sentence. Some sentences that researchers feed into FinBERT have come out with uncertainty in their sentiments. The model recognizes them as positive when the phrase is clearly negative. This is because in instances where sentences do not contain directional words, it cannot comprehend what connotation it has [48]. FinBERT also cannot detect sentiments from implicit sentences. These sentences do not explicitly state the notion to which they lead to. These types of sentences are general, and do not show up in factual sources such as newspapers or articles that share feelings about a topic. Evaluating implicit sentences can be tough even for people, but models that are not properly trained on this information suffer the most. They do not focus on the words but rather focus on if a word shows a specific feeling about a topic. This is a flaw that must be addressed to improve the quality of FinBERT's sentence analysis [49].

However, the positives outshine the disadvantages with using a sentiment analysis model such as FinBERT. The model can help one with learning about potential stocks with great returns. In one such study, the researchers bought the stocks with the greatest sentimental value generated by the model, and held onto the shares for five days. They fed several news articles to the robot, and created formulas to predict the price using the model's sentiment value. After the stocks had stopped trading on the last day, they compared the AI model's results with a classical human analysis. They found that in most cases, the stock's predicted value had been closer to the real price compared to alternative methods of finding a stock's value. This shows the accuracy of FinBERT and how it can be used to help the consumer investor in evaluating better stock picks. In most cases, it was only a couple of dollars away from the real stock's value [50].

The future outlook of FinBERT and using AI models as personal finance coaches seems optimistic and favorable. With the rapid progression of chatbots and the improvements made only in the last couple of years, it seems that other models made around the goal of finance can help investors to pick stocks that have the most likelihood of increasing. Overall, these models perform well and make money to cover inflation for most households, as most investors lose money in the stock market over a period of time. In a couple of years, models will be accurate and descriptive enough to where they will be able to buy stocks for us with greater return on investments than human finance managers.

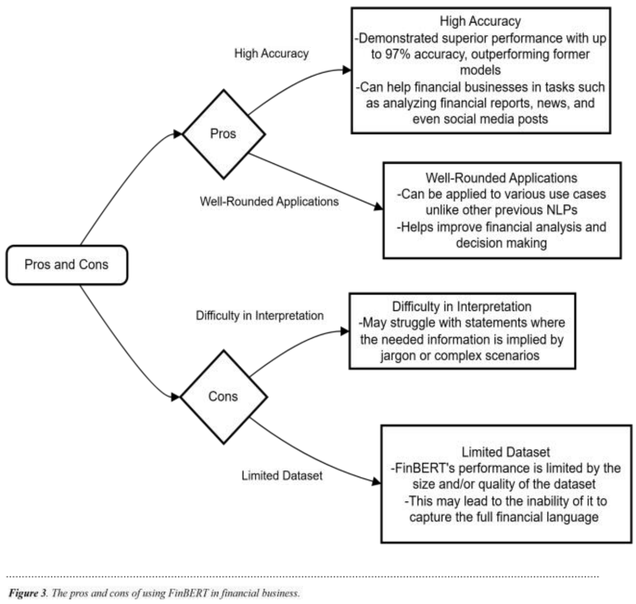

Figure 3. The pros and cons of using FinBERT in financial business.

5. Conclusion

In this review, we analyzed the integration of artificial intelligence in the financial world. With general knowledge of AI being trained on more data over time, we can assume that AI will be reliable in its measurements and can eventually help process financial data faster. FinBERT, a pre-trained NLP model specifically designed for analyzing sentiment in financial text, is based on the BERT language model and has been fine-tuned using large financial inputs to improve its performance in financial sentiment classification. FinBERT has high accuracy and overall well-rounded application, but a problem is its inability to detect sentiments in under-the-surface level statements. It has been trained on keywords that it analyzes, and if it cannot find those it misinterprets those sentences to the opposite of what they mean. However, dataset training, fine-tuning parameters, pre-processing, and contextual embeddings could be applied to help resolve these set-backs. Regardless, FinBERT still remains the most accurate financial sentiment analyzer model publicly available, and has an extremely high accuracy compared to its competitors. With a little bit more work, FinBERT could completely change and greatly enhance the performance of AI in finance.

Supplementary Material

Not applicable

Author contributions

A.M. writing – review & editing, writing – original draft, methodology, visualization, investigation. P.K. writing – review & editing, writing – original draft, methodology, investigation. R.C. writing – review & editing, methodology, writing – original draft, visualization, project administration, investigation. R.G. writing – review & editing, writing – original draft, methodology, visualization, investigation. V.G. writing – original draft, writing - review & editing, investigation. A.C., K.R. conceptualization, validation, writing - review & editing.

Competing financial interests

The authors declare no competing financial interests.

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