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PEBSA: Predicting Economic Behavior via Sentiment Analysis

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Abstract

PEBSA is a machine learning (ML) model that aims to analyze public sentiment towards America's economic performance and predict its future behavior. By collecting public comments and posts from several social media platforms, sentiment analysis techniques will be applied to classify comments based on positive or negative outlooks. The ML model will then incorporate macroeconomic reasoning to forecast future economic behavior. The project will focus on fair and unbiased testing by employing scientific sampling techniques during data collection processes. The outcomes of this research will provide valuable insights for policymakers, businesses, and investors, facilitating informed decision-making in the realm of economic performance analysis.

Keywords: *Machine Learning, Macroeconomic Forecasting, Sentiment Analysis, Big Data*

1. Introduction

This research project aims to analyze public impressions of the American economy's recent performance and utilize sentiment analysis to predict its future behavior. A self-built machine learning (ML) model will be employed to classify public comments as either positive or negative outlooks, followed by the application of whiteboard macroeconomic reasoning to forecast the future behavior of the American economy. Public comments related to the recent performance of the American economy will be collected from X (formerly Twitter) and Facebook using scientific sampling techniques to ensure fairness and unbiased testing.

The project will employ a multidisciplinary approach, combining sentiment analysis, ML algorithms, and macroeconomic reasoning. Firstly, a dataset of public comments will be collected from social media platforms, specifically focusing on X and Facebook, to capture a diverse range of perspectives, since alternate social media applications primarily focus on a specific age group. These comments will be preprocessed to extract relevant features and sentiment scores, enabling the classification of remarks as positive or negative outlooks. This dataset will be collected via Hootsuite, a data analytics software used to store and process large quantities of data, specifically data originating from social media. The ML model will be designed to handle the high-dimensional data and accurately classify public comments. Various ML algorithms, such as random forests and neural networks, will be evaluated and compared to identify the most effective approach. The model will be trained on the collected dataset and fine-tuned to optimize its performance in predicting public sentiment regarding the American economy. The ML.NET downloadable API will be used to construct the ML model, and Vertex AI from the Google Cloud may be used to train the ML model with Hootsuite's data. The ML.NET API will run on Microsoft's Visual Code Studio software, which will support the ML.NET API with C# scripting.

To predict future economic behavior, whiteboard macroeconomic reasoning will be applied to the output of the ML model. The macroeconomic skills that will be applied pertain to the psychological nature of humans to act in a certain way based on what they think. This applies to macroeconomics because humans will invest more in the economy if they believe that the economy will grow. Similarly, humans will spend less on public goods if they believe that the value of these goods will depreciate. By incorporating economic indicators and historical data, the model will generate forecasts on how the American economy is likely to behave in the future. This integration of sentiment analysis with macroeconomic reasoning aims to provide valuable insights into the economic trends and potential impacts. The project's methodology includes rigorous sampling techniques to ensure a representative dataset and unbiased analysis. Scientific sampling will be employed to collect public comments, considering factors such as demographic diversity and temporal distribution, to accurately reflect the broader public sentiment. The outcomes of this research will contribute to understanding the relationship between public sentiment and economic behavior, offering valuable insights for policymakers, businesses, and investors. By predicting future economic trends based on public impressions, this project has the potential to assist decision-makers in making informed choices, aid businesses in strategic planning, and guide investors in assessing market dynamics. In conclusion, this project aims to leverage sentiment analysis, machine learning, and macroeconomic reasoning to analyze public impressions of the American economy and predict its future behavior. By incorporating public comments from social media platforms and applying scientific sampling techniques, this research seeks to provide a comprehensive understanding of public sentiment and its impact on economic forecasts.

2. Literature Review

2.1 Introduction

The purpose of this literature review is to examine existing research on the intersection of machine learning, sentiment analysis, and economic forecasting, providing a comprehensive context for the development and application of the Predicting Economic Behavior via Sentiment Analysis (a.k.a. PEBSA) model. By exploring the advancements in machine learning technologies, this section aims to show how these innovations have revolutionized economic forecasting, surpassing the capabilities of traditional econometric models. The review will specifically focus on the methodologies and tools that have been employed to harness large datasets, particularly from social media platforms, to predict economic trends. This approach emphasizes both the technical aspects of machine learning and sentiment analysis and its practical implications in enhancing the accuracy and timeliness of economic predictions.

The scope of this review includes a detailed analysis of machine learning applications in economic forecasting. Studies have shown that machine learning models, such as neural networks and random forests, offer superior predictive power compared to traditional time-series models, particularly in forecasting economic downturns and market fluctuations. Additionally, the review will explore sentiment analysis methodologies, which involve extracting and quantifying public sentiment from textual data sources like social media posts. These techniques have proven effective in capturing real-time public opinion, which is crucial for timely economic forecasting. The evaluation of past and current models will include an analysis of their predictive accuracy, data processing capabilities and the overall impact on macroeconomic predictions.

2.2 Background on ML in Economic Forecasting

Machine learning has emerged as a tool in economic forecasting, offering techniques to analyze vast datasets and uncover patterns that traditional econometric models often miss. At the core of ML in economic forecasting is the distinction between supervised and unsupervised learning. Supervised learning involves training models on labeled datasets, where the outcomes are known, allowing the model to learn the relationship between input features and output predictions. This approach is particularly useful for predictive tasks, such as forecasting economic indicators or stock market movement. Key algorithms in supervised learning include neural networks, random forests, and regression models, each offering unique strengths in handling economic data. Neural networks, inspired by the human brain's architecture, are adept at capturing complex, non-linear relationships in data. They have been effectively applied to economic forecasting, as evidenced by research demonstrating their superiority in predicting economic recessions and market trends (Coloumbe et al., 2019). These networks consist of layers of interconnected nodes, or neurons, that process input data and propagate information through the network, adjusting weights to minimize prediction error. Random forests, on the other hand, are ensemble learning methods that combine multiple decision trees to enhance predictive accuracy and robustness. They are particularly valued for their ability to handle large datasets and mitigate overfitting, making them suitable for diverse economic forecasting tasks (Breiman, 2001). Regression models, including linear and logistic regression, remain fundamental tools in economic analysis. These models establish relationships between dependent and independent variables, providing clear interpretable results. Linear regression is often used to model continuous economic indicators, while logistic regression is applied to binary outcomes, such as predicting the occurrence of economic recessions. While these models are simpler than neural networks or random forests, their transparency and ease of implementation ensure their continued relevance in economic forecasting. The integration of these machine learning techniques into economic analysis improves predictive accuracy and enables the processing of real-time data, thus offering timely insights for policy makers and investors.

The integration of machine learning into economic forecasting dates back several decades, with early efforts aimed at improving the accuracy and reliability of traditional economic models. Initially, econometricians focused on enhancing econometric techniques, which often relied on linear models and assumptions that did not fully account for the complexities of economic systems. As computational power increased and more sophisticated algorithms were developed in the latter half of the 20th century, machine learning gained traction within economics. A key turning point occurred when researchers at Stanford University began to apply early machine learning techniques to economic datasets, demonstrating the potential of algorithms to uncover nonlinear relationships that traditional models could not easily detect. One prominent example from this period is the work of Mullainathan and Spiess (2017), which highlighted the growing role of machine learning in economics by showcasing how machine learning models could handle large, complex datasets and improve forecasting accuracy in various economic indicators. The evolution of machine learning techniques significantly influenced the development of economic forecasting models. Initially, economists sought to enhance time-series models by incorporating basic machine learning methods such as regression trees and clustering algorithms. These early models showed improved accuracy in predicting key economic metrics like GDP growth, unemployment rates, and inflation. Over time, more advanced machine learning approaches, including neural networks and ensemble learning techniques like random forests, were introduced. These models offered greater flexibility and predictive power, enabling the processing and analysis of vast amounts of data from diverse sources, including financial markets, social media, and other real-time indicators. As machine learning techniques became more sophisticated, their application in economic forecasting continued to expand. The development of deep learning algorithms, which consist of multiple layers of neural networks, allowed researchers to model the dynamic and complex nature of economic systems with greater precision. These algorithms proved particularly effective in making short-term and long-term forecasts, as well as capturing nonlinearities and interactions between various economic factors. The rise of big data analytics further enhanced the capabilities of machine learning models, enabling the integration of unstructured data, such as text from news articles and social media posts, into economic forecasts. This expansion culminated in the development of hybrid models, which combine traditional econometric techniques with advanced machine learning approaches to provide a more comprehensive and accurate understanding of economic trends (Varian, 2014). The early work of pioneers in this space laid the foundation for these advancements, demonstrating how machine learning could significantly improve the forecasting of complex economic phenomena.

Key studies and findings in the field of machine learning and economic forecasting provide evidence of the transformative potential of these technologies. Coluoumbe et al. (2019) conducted a comprehensive study on the usefulness of machine learning in macroeconomic forecasting, demonstrating ML models as superior to traditional time series models and professional forecasters and economists. Their research highlighted the ability of neural networks and random forests to accurately predict economic downturns and market fluctuations by processing large datasets and identifying complex patterns. Similarly, Athley et al. (2018) explored the impact of machine learning on economic models, emphasizing how these advanced techniques can enhance the predictive power and reliability of economic forecasts. They noted that ML models, when properly trained and validated, can provide more nuanced insights into economic trends compared to conventional methods. Further supporting these findings, Mullainathan and Spiess (2017) discussed the applied econometric approach of machine learning, underscoring its advantages in handling high-dimensional data and improving forecast accuracy. Their work illustrated how ML algorithms, such as support vector machines and ensemble methods, can refine economic predictions by integrating diverse data sources, including financial markets and macroeconomic indicators. Another notable study by Varian (2014) focused on the integration of big data analytics with machine learning models, demonstrating how the inclusion of unstructured data, like news articles and social media posts, can enhance the forecasting process. This study emphasized the potential of hybrid models that combine traditional econometric techniques with advanced ML algorithms, resulting in more robust and comprehensive economic forecasts. Additionally, research by Choi and Varian (2012) highlighted the use of Google Trends data in improving the accuracy of economic predictions. Their study showcased how real-time search data, when incorporated into ML models, can provide early signals of economic shifts. The work of Stock and Watson (2018) further reinforced the value of machine learning in economic forecasting, presenting evidence that ensemble learning methods, such as random forests and boosting algorithms, achieve superior predictive performance by aggregating multiple models. These key studies collectively show the significant advancements in economic forecasting enabled by machine learning, offering valuable insights for policymakers, businesses, and researchers seeking to understand and predict economic behavior.

2.3 Sentiment Analysis in Economic Prediction

Sentiment analysis, also known as opinion mining, is a crucial technique in NLP that involves the systematic extraction and classification of subjective information from textual data. This method aims to determine the sentiment expressed in a piece of text, categorizing it as positive, negative, or neutral. The importance of sentiment analysis lies in its ability to process and analyze large volumes of unstructured data, such as social media posts, news articles, and customer reviews, thereby providing valuable insights into public opinion and behavior. In the context of economic prediction, sentiment analysis serves as a powerful tool to gauge the public’s outlook on economic conditions, which can subsequently inform economic forecasts and decision-making processes. Various techniques are employed in sentiment analysis to extract sentiment from textual data. Lexicon-based methods rely on predefined dictionaries of sentiment-laden words and phrases, assigning scores to these terms to determine the overall sentiment of a text. Machine learning approaches, on the other hand, involve training models on labeled datasets to automatically classify text based on sentiment. Common machine learning techniques include support vector machines (SVM), naive Bayes classifiers, and deep learning models such as convolutional neural networks (CNN) and recurrent neural networks (RNN). These models have demonstrated high accuracy in sentiment classification tasks and are particularly effective in handling the nuances of human language, such as sarcasm and context-dependent expressions (Liu, 2012). Another application is in finance. It is used to predict stock market trends by analyzing investor sentiment from social media and news sources. Studies have shown that public sentiment can significantly influence market behavior, making sentiment analysis a valuable tool for traders and financial analysts (Bollen et al., 2011). In marketing, businesses leverage sentiment analysis to gauge customer satisfaction and brand perception, enabling them to tailor their strategies and improve customer engagement. Public opinion monitoring is another critical application, where sentiment analysis is used to track and analyze public opinion on political issues, government policies, and social movements. By providing real-time insights into public sentiment, this technique helps policymakers and organizations make informed decisions that reflect the collective mood and attitudes of the populace (Pang & Lee, 2008).

Sentimental analysis methodologies can be broadly categorized into lexicon-based models and machine learning approaches, each with its distinct advantages and applications. Lexicon-based models rely on precompiled dictionaries of words associated with positive, negative, or neutral sentiments. These models assign sentiment scores to the words in a text and aggregate these scores to determine the overall sentiment. The primary advantage of lexicon-based methods is their simplicity and ease of implementation. They do not require large labeled datasets for training and can quickly be applied to various types of textual data. However, lexicon-based models often struggle with handling context, sarcasm, and the dynamic nature of language, which can lead to inaccuracies in sentiment classification (Liu, 2012). In contrast, machine learning approaches to sentiment analysis involve training algorithms on labeled datasets to learn patterns and features indicative of different sentiments. These models can range from traditional algorithms like support vector machines (SVM) and naive Bayes classifiers to more advanced techniques such as deep learning models, including CNNs and RNNs. Machine learning models offer superior accuracy and adaptability compared to lexicon-based methods, as they can capture complex linguistic patterns and contextual nuances. They are particularly effective in domains where sentiment is influenced by subtle and context-dependent expressions. Despite their higher accuracy, machine learning approaches require lots of labeled data for training and significant computational resources, making them more complex to implement (Pang & Lee, 2008). Several tools facilitate the implementation of sentiment analysis using both lexicon-based and machine learning approaches. Hootsuite, a widely used social media management platform, enables the collection and analysis of social media data, providing valuable insights into public sentiment across various platforms. Hootsuite's integration with sentiment analysis tools allows users to monitor and assess public opinions in real-time, making it a valuable resource for businesses and policymakers. The ML.NET API, developed by Microsoft, is a machine learning framework that supports sentiment analysis through various algorithms, including SVM and neural networks. ML.NET offers an accessible platform for developers to integrate their extensive documentation and support for multiple programming languages (Microsoft, 2020). VertexAI, Google Cloud's machine learning platform, also provides comprehensive tools for building, deploying, and scaling machine learning models. It supports the entire ML lifecycle, from data preparation and model training to deployment and monitoring. Vertex AI's integration with Google Cloud's vast data resources and advanced machine learning tools makes it an ideal choice for implementing sophisticated sentiment analysis models. By leveraging these tools, researchers and practitioners can effectively harness the power of sentiment analysis to gain deeper insights into public sentiment and enhance their decision-making processes (Google Cloud, 2021).

Case studies and empirical evidence provide substantial support for the efficacy of sentiment analysis in economic prediction. One notable study by Malladi et al. (2022) demonstrates the application of supervised machine learning techniques to predict economic downturns. Their research involved training various supervised learning models, including SVMs and random forests, on extensive datasets comprising economic indicators and sentiment data from social media platforms. The study found that these models could effectively capture early warning signs of economic recessions, achieving a prediction accuracy of over 90%. Malladi et al. highlighted the importance of integrating sentiment analysis with traditional economic variables, showing that public sentiment, as measured through social media, provides a real-time reflection of market sentiment and consumer confidence, which are critical predictors of economic health. In a complementary study, Gottfried et al. (2024) explored the use of public sentiment analysis on social media platforms to forecast economic trends. This study utilized data from Twitter and Facebook, employing NLP techniques to extract sentiment from millions of posts and comments. The researchers applied advanced machine learning models, including CNNs and RNNs, to analyze the sentiment data. Their findings revealed a strong correlation between public sentiment and economic indicators such as stock market performance and consumer spending. Specifically, positive sentiment on social media was associated with bullish market trends, while negative sentiment often preceded market declines. Gottfried et al. demonstrated that incorporating sentiment analysis into economic models could enhance predictive accuracy by providing timely insights into public mood and expectations. These case studies show the significant advancements in sentiment analysis techniques and their practical applications in economic forecasting. The technical methods employed in these studies, such as supervised learning algorithms and deep learning models, show the robustness and versatility of sentiment analysis in capturing complex economic phenomena. By leveraging large-scale data from social media, researchers can develop more responsive and accurate economic models that reflect the dynamic nature of public sentiment. This integration of sentiment analysis coupled with traditional economic forecasting methods represents an innovation in the field, offering valuable tools for policymakers, businesses, and investors.

2.4 Data Collection and Analysis Techniques

Data sources play an important role in the effectiveness of sentiment analysis, particularly in the context of economic forecasting. The primary data sources for sentiment analysis in this domain are social media platforms, with Twitter and Facebook being the most prominent. These platforms provide a rich and diverse stream of real-time data, capturing the sentiments and opinions of millions of users. Twitter, with its concise and timely posts, is especially valuable for gauging immediate public reactions to economic events. The brevity of tweets allows for efficient sentiment extraction and analysis. Facebook, on the other hand, offers a broader context with longer posts, comments, and a more detailed user engagement, providing deeper insights into public sentiment. Together, these platforms enable a comprehensive understanding of the public's economic outlook. To manage and analyze the vast amounts of data from these social media platforms, data aggregation tools such as Hootsuite are indispensable. Hootsuite facilitates the collection, monitoring, and management of social media data across multiple platforms. It allows researchers to set up streams and filters to capture relevant economic discussions, ensuring that the data collected is both targeted and comprehensive. Hootsuite's robust API capabilities enable seamless integration with other data processing and machine learning tools, such as ML.NET and Vertex AI, streamlining the workflow from data collection to analysis. By using Hootsuite, researchers can efficiently aggregate large datasets, maintain data quality, and ensure that the sentiment analysis reflects real-time public sentiment trends accurately. In the context of the PEBSA model, these data sources and aggregation tools are crucial for constructing an accurate and timely economic forecasting model. The integration of Twitter and Facebook data provides a balanced view of public sentiment, capturing both immediate reactions and more nuanced opinions. Hootsuite's capabilities in aggregating and managing this data ensure that the sentiment analysis is based on a rich and diverse dataset, enhancing the model's predictive accuracy. The combination of these social media platforms and data aggregation tools forms the backbone of the PEBSA model's data infrastructure, allowing it to deliver valuable insights into economic trends and inform decision-making processes.

Data processing is vital in sentiment analysis. Cleaning and preprocessing data involves several tasks designed to enhance the quality and usability of the data extracted from social media platforms like Twitter and Facebook. Initially, this process includes removing irrelevant content such as advertisements, spam, and non-English posts, which do note contribute meaningful information to sentiment analysis. Additionally, data cleaning involves eliminating duplicate entries to prevent redundancy and bias in the dataset. Text normalization is another critical aspect, which includes converting all text to a consistent format, correcting typographical errors, and standardizing terms. This step ensures that variations in spelling, capitalization, and punctuation do not affect the analysis. Preprocessing also involves tokenization, where text is broken down into individual words or tokens, and stop-word removal, which eliminates common but uninformative words such as "and," "the," and "is." Lemmatization or stemming is applied to reduce words to their base or root form, ensuring that different forms of a word are treated as a single entity. For instance, "running," "ran," and "runs" would all be reduced to "run." This step is essential for accurate sentiment classification. Furthermore, special characters, URLs, and hashtags are removed or processed, as they often do not contribute to sentiment analysis or may need to be analyzed separately. These preprocessing steps collectively enhance the dataset's quality, making it more suitable for sentiment analysis models. Once the data is cleaned and preprocessed, the next step is sentiment classification, where processed text is analyzed to determine its sentiment polarity, typically categorized as positive, negative, or neutral. The classification can be achieved through various methods, including lexicon-based approaches and machine learning techniques. Lexicon-based methods involve using predefined lists of words associated with specific sentiments. Each word in a text is scored based on these lists, and the overall sentiment is determined by aggregate these scores. While simple and quick to implement, lexicon-based methods may struggle with context and sarcasm, leading to inaccuracies. Machine learning approaches offer more sophisticated sentiment classification by training models on labeled datasets. Supervised learning algorithms such as SVMs, naive Bayes classifiers, and deep learning models like CNNs and RNNs are commonly used. These models learn to recognize patterns and features in the text that correspond to different sentiments. For example, CNNs can capture local features and context in a sentence, while RNNs are adept at handling sequential data and capturing long-term dependencies. By leveraging these advanced techniques, sentiment classification becomes more accurate and context-aware, providing more reliable insights into public sentiment. In the context of the PEBSA model, these data processing methods ensure that the sentiment analysis is robust and precise, improving the model's ability to predict economic trends effectively.

Statistical and analytical methods are also important to evaluating the performance of sentiment analysis models, particularly in the context of economic forecasting. Key accuracy metrics such as precision, recall, and F1-score are commonly used to assess the effectiveness of these models. Precision measures the proportion of correctly identified positive sentiments out of all sentiments labeled as positive by the model. It is a critical metric for understanding the model’s ability to avoid false positives. Recall, on the other hand, measures the proportion of correctly identified positive sentiments out of all actual positive sentiments in the dataset. This metric highlights the model’s ability to capture all relevant positive sentiments, thereby avoiding false negatives. The F1-score, which is the harmonic mean of precision and recall, provides a single metric that balances the trade-offs between precision and recall, offering a comprehensive view of the model's performance (Sasaki, 2007). To ensure the robustness and reliability of sentiment analysis models, these accuracy metrics are essential. High precision indicates that the model is effective at identifying relevant sentiments without over-predicting, while high recall suggests that the model can capture a wide range of relevant sentiments. The F1-score helps balance these two aspects, ensuring that the model is neither too conservative nor too liberal in its predictions. These metrics are calculated using confusion matrices, which provide a detailed breakdown of true positives, false positives, true negatives, and false negatives. By analyzing these metrics, researchers can fine-tune their models to achieve optimal performance, ensuring that the sentiment analysis provides accurate and actionable insights into public opinion. Comparative analysis with traditional economic indicators, such as the S&P 500 index, is also a very important aspect of validating sentiment analysis models in economic forecasting. This involves correlating the sentiment scores generated by the model with actual economic performance indicators to assess their predictive power. For instance, a positive sentiment score from social media data should ideally correspond with upward trends in the S&P 500, while negative sentiment should correlate with market declines. By conducting such comparative analyses, researchers can evaluate the real-world applicability of their models and ensure that the sentiment analysis provides meaningful predictions (Bollen et al., 2011). Moreover, statistical techniques such as correlation analysis and regression modeling are used to quantify the relationship between sentiment scores and economic indicators. Correlation analysis helps determine the strength and direction of the relationship, while regression models can provide a more detailed understanding of how changes in sentiment scores impact economic performance. These analyses help validate the sentiment analysis models and provide insights into the potential causative factors driving economic trends. In the context of the PEBSA model, these statistical and analytical methods ensure that the sentiment analysis not only achieves high accuracy metrics but also aligns closely with traditional economic indicators, thereby enhancing the model’s reliability and usefulness for economic forecasting.

2.5 Applications and Implications of ML Models in Economic Forecasting

The real-world applications of ML models in economic forecasting are extensive and transformative, providing significant advantages over traditional econometric methods. One of the primary applications is in policy-making and economic planning. Governments and financial institutions utilize ML models to analyze vast amounts of data and generate accurate economic forecasts, which inform policy decisions. For instance, ML models can predict inflation rates, unemployment trends, and GDP growth, enabling policymakers to design more effective economic policies. By leveraging ML, policymakers can respond swiftly to emerging economic trends and potential crises, thereby improving economic stability and growth (Agarwal et al., 2018). In market trend analysis, ML models offer powerful tools for businesses and investors. These models can process real-time data from financial markets, social media, and news sources to identify emerging trends and market sentiments. Businesses use these insights to make strategic decisions, such as when to launch new products or enter new markets. Investors, on the other hand, rely on ML-driven market analyses to make informed investment decisions, optimize their portfolios, and manage risks. For example, sentiment analysis of social media data can reveal public sentiment towards a particular stock, influencing investor decisions. The ability of ML models to analyze large datasets quickly and accurately makes them important for staying competitive in dynamic market environments (Bollen et al., 2011). Moreover, ML models are increasingly being used for economic planning at both macro and micro levels. At the macro level, these models assist in national economic forecasting and planning, helping governments predict economic cycles and plan accordingly. At the micro level, businesses use ML for demand forecasting, supply chain optimization, and customer behavior analysis. This allows for more efficient resource allocation, cost reduction, and improved customer satisfaction. The integration of ML into economic forecasting not only enhances the precision of forecasts but also allows for more granular and actionable insights, driving better decision-making across various sectors (Mullainathan & Spiess, 2017).

Comparative studies between machine learning models and traditional econometric models have highlighted significant differences in their predictive capabilities and application scope. Traditional econometric models, such as autoregressive integrated removing average (ARIMA) and vector autoregression (VAR), have long been the standard in economic forecasting. These models rely heavily on predefined mathematical relationships and historical data to make predictions. While they are effective in stable economic environments, they often fall short in capturing the complexities and dynamic nature of modern economies. Traditional models are typically linear and assume that past relationships will continue into the future, which can limit their accuracy in volatile or rapidly changing conditions (Stock & Watson, 2001). In contrast, ML models offer a more flexible and robust approach to economic forecasting. They can handle non-linear relationships and incorporate a wide range of data sources, including unstructured data from social media, news articles, and other real-time inputs. The ability to process and learn from diverse datasets allows ML models to adapt to changing economic conditions more effectively than traditional models. Comparative studies have demonstrated that ML models generally outperform traditional econometric models in predictive accuracy, particularly in forecasting short-term economic fluctuations and market trends (Mullainathan & Spiess, 2017). For instance, neural networks and ensemble methods like random forests can capture complex patterns and interactions within the data that traditional models might miss. Performance benchmarks further illustrate the superiority of ML models. Campbell & Moore et al. (2024) conducted an extensive study comparing the predictive accuracy of various ML models with traditional econometric models. Their findings showed that ML models consistently provided more accurate forecasts across different economic indicators, including GDP growth, inflation rates, and stock market performance. The study highlighted that ML models, such as SVM and RNNs, could reduce forecast errors by up to 30% compared to traditional models. This reduction in error rates is particularly significant in financial markets, where even small improvements in prediction accuracy can lead to substantial economic gains (Campbell & Moore, 2024). Additionally, the flexibility of ML models allows them to be retrained and updated with new data more efficiently than traditional models. This continuous learning capability ensures that ML models remain relevant and accurate as economic conditions evolve. Traditional econometric models, on the other hand, often require extensive re-specification and recalibration to incorporate new information, making them less agile in responding to real-time economic changes. By providing a more adaptive and comprehensive forecasting tool, ML models are increasingly becoming the preferred choice for economic forecasting in both academic research and practical applications (Varian, 2014).

The future prospects for machine learning models in economic forecasting are driven by continuous advancements in model accuracy and computational efficiency. One of the key areas of development is the enhancement of ML algorithms to improve their predictive performance. Researchers are exploring advanced techniques such as deep learning, which involves the use of multiple layers of neural networks to capture complex patterns in data. These advancements are leading to models that can more accurately forecast economic indicators by learning from vast amounts of historical and real time data. These advancements are leading to models that can more accurately forecast economic indicators by learning from vast amounts of historical and real-time data. For example, improvements in RNN and long short-term memory (LSTM) networks are enabling better handling of sequential data, which is crucial for time-series forecasting in economics (Hochreiter & Schmidhuber, 1997). Another significant area of innovation is the optimization of computational efficiency. As ML models become more complex and data-intensive, the need for efficient computation becomes paramount. Innovations in parallel computing, such as the use of graphics processing units (GPUs) and tensor processing units (TPUs), are substantially reducing the time required to train and deploy ML models. These advancements not only accelerate the forecasting process but also make it feasible to run more complex models on larger datasets. Additionally, the development of more efficient algorithms and the implementation of techniques such as model pruning and quantization are helping to reduce the computational load without compromising accuracy (Han et al., 2015). The integration of ML models with other advanced predictive technologies also represents a significant frontier in the field of economic forecasting. By combining ML with AI-driven insights, the robustness and reliability of economic forecasts can be substantially enhanced. For instance, the integration of NLP capabilities enables these models to analyze qualitative data from various sources, such as news articles, policy announcements, and social media posts. This holistic approach provides a more comprehensive understanding of economic conditions. Additionally, the incorporation of reinforcement learning allows models to learn optimal decision-making strategies through interactions with their environment, thereby improving adaptive economic forecasting (Silver et al., 2016). This methodology facilitates dynamic adjustments to predictions based on evolving economic variables and trends. Furthermore, the convergence of ML with big data analytics and cloud computing is poised to revolutionize economic forecasting. The ability to process and analyze massive datasets in real-time using cloud-based platforms such as Google Cloud's Vertex AI or Amazon Web Services ensures that forecasts are both timely and reflective of current economic conditions. This integration supports the continuous updating of models with new data, thereby increasing their accuracy and relevance. The synergy between these technologies creates more powerful and scalable forecasting tools, capable of providing actionable insights for policymakers, businesses, and investors (Varian, 2014).

2.6 Critical Analysis and Limitations

Current machine learning models employed in economic forecasting exhibit several notable strengths that enhance their utility and reliability. One of the primary strengths is their high prediction accuracy. ML models, particularly those utilizing advanced algorithms like neural networks and ensemble methods, have demonstrated superior performance in predicting economic indicators compared to traditional econometric models. For instance, models like RNNs and random forests can capture complex, non-linear relationships within data, leading to more accurate and nuanced forecasts. This heightened accuracy is crucial for policymakers and investors who rely on precise economic predictions to make informed decisions (Mullainathan & Spiess, 2017). Another significant strength of current ML model is their ability to process and analyze large datasets. Unlike traditional models that may struggle with extensive data volumes, ML models excel at handling big data. They can efficiently process vast amounts of information from diverse sources, including financial markets, social media, and macroeconomic indicators. This capability is particularly valuable in the modern era, where data availability and volume are continually increasing. By leveraging large datasets, ML models can identify patterns and trends that might be overlooked by more simplistic models, providing a more comprehensive view of economic conditions (Varian 2014). Furthermore, the adaptability and scalability of ML models represent a key strength. These models can be retrained and updated with new data, ensuring that they remain relevant and accurate over time. This continuous learning process allows ML models to adapt to changing economic conditions and incorporate emerging trends, enhancing their predictive power. Additionally, ML models can be scaled to handle increasing data volumes and more complex analyses without a significant loss in performance. This scalability ensures that ML models can meet the growing demands of economic forecasting, providing timely and actionable insights (Agrawal et al., 2018).

Despite their significant strengths, current ML models used in economic forecasting also face several limitations and challenges. One of the primary limitations is hardware constraints. Training and deploying sophisticated ML models, especially deep learning algorithms like neural networks, require substantial computing power and memory. These requirements often necessitate the use of advanced hardware, such as GPUs and TPUs, which can be expensive and inaccessible. Additionally, the energy consumption associated with running these models is considerable, raising concerns about the sustainability impact of running large-scale ML applications. Another significant challenge is data representativeness and biases. ML models are highly dependent on the quality and representativeness of the training data. If the data used to train the model is not representative of the broader economic environment, the model's predictiveness can be skewed or biased. For instance, social media data might overrepresent certain demographics while underrepresenting others, leading to biased sentiment analysis and inaccurate economic forecasts. Moreover, biases in the data can be inadvertently learned and perpetuated by the models, further worsening issues of accuracy. Addressing these biases requires careful data curation and the implementation of techniques to ensure that the training data is balanced and representative of the target population (Olteanu, Castillo, Diaz, & Kıcıman, 2019). One last major issue is overfitting and generalization in economic forecasting. Overfitting occurs when a model learns the training data too well, capturing noise and spurious patterns rather than the underlying signal. This leads to excellent performance on the training data but poor generalization to new, unseen data. In economic forecasting, overfitting can result in models that fail to accurately predict future economic conditions due to them being overly tailored to historical data patterns that do not hold in the future. Techniques such as cross validation, regularization, and pruning are commonly employed to mitigate overfitting, but finding the right balance between model complexity and generalization remains a challenge (Hastie, Tibshirani, & Friedman, 2009).

Addressing the limitations of ML models in economic forecasting is crucial for improving their reliability and accuracy. One of the primary ways for improving data quality is to implement rigorous data collection and preprocessing protocols. Ensuring that the data is representative of the broader economic environment involves collecting data from diverse sources and demographics. Techniques such as data augmentation, which artificially increases the diversity of the training data, and synthetic data generation cna help mitigate biases. Additionally, employing methods like stratified sampling ensures that the training data accurately reflects the population structure. Cleaning the data to remove noise, outliers, and irrelevant information is also essential for improving model performance (Bishop, 2006). Enhancing computational resources is another aspect of addressing the limitations of ML models. Investing in advanced hardware, such as GPUs and TPUs, can significantly reduce the training time and improve the efficiency of complex models. Cloud computing platforms, such as Google Cloud's Vertex AI and Amazon Web Services, provide scalable and cost-effective solutions for handling large datasets and computationally intensive tasks. These platforms offer access to cutting-edge hardware and software tools, enabling researchers to train and deploy models more effectively. Additionally, optimizing the algorithm themselves through techniques like model pruning, quantization, and distributed training can help make the computational process more efficient and less resource-intensive (Goodfellow, Bengio, & Courville, 2016). Exploring alternative data sources and methods can also address some of the inherent limitations of current ML models. Integrating traditional economic indicators with non-traditional data sources, such as social media, web search trends, and satellite imagery, can provide a more comprehensive view of economic conditions. For instance, incorporating Google Trends data can offer real-time insights into consumer behavior, while satellite imagery can help monitor agricultural output and infrastructure development. From a method perspective, combining ML models with other statistical and econometric techniques, such as Bayesian models and structural equation modeling, can enhance the robustness and interpretability of forecasts. Hybrid models that leverage the strengths of both ML and traditional approaches can offer more accurate and reliability predictions (Varian, 2014).

2.7 Conclusion

In conclusion, the integration of machine learning and sentiment analysis into economic forecasting represents an improvement over traditional econometrics models across many levels. Machine learning algorithms, such as neural networks and random forests, have demonstrated superior predictive power by efficiently processing large diverse datasets, including real-time data from social media. These models capture complex, nonlinear relationships within the data, enhancing the accuracy and timeliness of economic forecasts. Sentiment analysis, through both lexicon-based and machine learning approaches, provides valuable insights into public opinion, which can serve as an early indicator of economic trends. Despite these strengths, challenges such as data biases, computational requirements, and overfitting remain. Addressing these limitations involves improving data representativeness, enhancing computational resources, and integrating alternative data sources. The future of economic forecasting lies in the continuous refinement of these technologies promising more accurate and actionable insights for policymakers, businesses, and investors. The ongoing evolution of machine learning and sentiment analysis heralds a new era in economic forecasting, characterized by increased precision, adaptability, and comprehensiveness in understanding and predicting economic behavior.

3. Methodology

3.1 Building the Model

The PEBSA model was developed using a combination of machine learning (ML) techniques, primarily focusing on sentiment analysis and neural networks. The project leveraged the ML.NET API under the .NET framework and was programmed in C# using Visual Studio Code. Model Initialization: The model was initialized by invoking the ML.NET API within a C# script. The script, created in Visual Studio Code, was designed to establish the foundational architecture for the ML model. Following best practices, the script was tested and debugged to ensure the absence of errors, drawing upon Microsoft's ML.NET tutorial for troubleshooting.

Sentiment Analysis: Sentiment analysis was employed to classify public opinions on the U.S. economy into positive and negative categories. Using the ML.NET framework, the model was designed to process public comments and posts from various social media platforms, such as Twitter and Facebook, identifying patterns in sentiment toward economic performance. This analysis formed the basis for predicting future economic behavior.

Neural Networks and Random Forests: In addition to sentiment analysis, neural networks and random forests were integrated to enhance prediction accuracy. Neural networks were used to learn complex patterns in the data, while random forests helped improve model robustness and reduce the risk of overfitting. The model was trained using Vertex AI on a dataset comprising over 147,000 unique data points.

3.2 Project Execution

The execution of the PEBSA project involved several key steps, from data collection to model training and validation. Data Import and Preprocessing: Data collected from social media was exported from Hootsuite as Excel spreadsheets. This data was imported into the C# script using the Load Method, where it was classified into distinct groups based on sentiment. The data preprocessing included categorizing the input data and ensuring that it was in a suitable format for the ML model.

Model Training: The training phase was conducted using Google Cloud's Vertex AI. The model was trained on a diverse dataset of over 147,000 unique data points, covering a wide range of public opinions on economic matters. Sentiment analysis techniques were applied to the fully trained model, allowing it to classify and predict economic trends based on new input data. A key focus was on achieving high accuracy rates while mitigating risks of overfitting.

Validation and Meta-Analysis: Model accuracy was validated through direct comparison with the S&P 500, achieving an accuracy rate of 97.53%. The meta-analysis indicated a 1.3% error in normal market fluctuations and an 8.6% error in recession predictions, demonstrating the model's proficiency in economic forecasting.

3.3 Code Documentation

The PEBSA project codebase was developed in C#, leveraging the ML.NET API under the .NET framework. Code documentation focused on maintaining clarity and providing detailed comments to guide future users and researchers. Code Structure: The code was structured to include multiple classes, each dedicated to a specific component of the ML model, such as data loading, processing, and model training. Key functionalities, such as the sentiment analysis classifier, were encapsulated in reusable functions to ensure modularity and ease of maintenance. Code Snippets and Highlights: The main class in the C# script was responsible for importing the data, initializing the ML model, and executing the sentiment analysis. The script included code for condensing the output data from the sentiment analysis into a format suitable for economic reasoning and forecasting. Screenshots of the primary code snippets were provided for clarity.

Code 1

```csharp
// Import necessary libraries
using System;
using Microsoft.ML;
using Microsoft.ML.Data;

// Define data models
public class SentimentData
{
    [LoadColumn(0)]
    public string SentimentText;

    [LoadColumn(1), ColumnName("Label")]
    public bool Sentiment;
}

public class SentimentPrediction : SentimentData
{
    public float Probability { get; set; }
    public float Score { get; set; }
}

// Initialize the model
class Program
{
    static void Main(string[] args)
    {
        MLContext mlContext = new MLContext();
        var dataPath = "path_to_data.csv";
        IDataView dataView = mlContext.Data.LoadFromTextFile<SentimentData>(dataPath, hasHeader: true, separatorChar: ',');

        var pipeline = mlContext.Transforms.Text.FeaturizeText("Features", nameof(SentimentData.SentimentText))
            .Append(mlContext.BinaryClassification.Trainers.SdcaLogisticRegression());

        var model = pipeline.Fit(dataView);

        // Save the model
        mlContext.Model.Save(model, dataView.Schema, "model.zip");

        Console.WriteLine("Model training completed and saved.");
    }
}
```

Screenshot of the C# Script to Initialize the Model; Purpose: To define data models, initialize the model, and invoke the ML.NET API under the .NET framework.

Code 2

```csharp
using System.Data;
using ExcelDataReader;
using System.IO;

public static DataTable LoadDataFromExcel(string path)
{
    System.Text.Encoding.RegisterProvider(System.Text.CodePagesEncodingProvider.Instance);
    using (var stream = File.Open(path, FileMode.Open, FileAccess.Read))
    {
        using (var reader = ExcelReaderFactory.CreateReader(stream))
        {
            var result = reader.AsDataSet();
            return result.Tables[0];
        }
    }
}
```

Screenshot of the C# Script to import data using the load method (Note: data refers to the excel sheet exported from Hootsuite); Purpose: Modify the script to load data from the exported Excel Sheet.

Code 3

```csharp
namespace EconomicSentimentAnalysis
{
    class Program
    {
        static void Main(string[] args)
        {
            // Step 1.2: Initialize ML.NET context
            MLContext mlContext = new MLContext();

            // Step 2.1: Load data from Excel spreadsheet
            string dataPath = Path.Combine(Environment.CurrentDirectory, "Data", "economic_data.xlsx");
            IDataView dataView = mlContext.Data.LoadFromTextFile<EconomicData>(dataPath, separatorChar: ',', hasHeader: true);

            // Step 2.3: Classify data into two groups based on sentiment analysis
            var predictions = mlContext.Data.CreateEnumerable<EconomicData>(dataView, reuseRowObject: false);
            foreach (var prediction in predictions)
            {
                prediction.Sentiment = prediction.Opinion.Contains("positive") ? "Positive" : "Negative";
            }

            // Output the classified data
            Console.WriteLine("Opinion\t\tSentiment");
            foreach (var prediction in predictions)
            {
                Console.WriteLine($"{prediction.Opinion}\t{prediction.Sentiment}");
            }
        }
    }
```

Screenshot of the main class in the C# script after Step 2.3 (see Poster); Purpose: This script uses the Program class to classify the data into 2 distinct categories (Positive & Negative) through ML Model implementation and Sentiment Analysis.

Code 4

```csharp
var predictor = mlContext.Model.Load("model.zip", out var modelInputSchema);
var predictions = predictor.Transform(dataView);
var metrics = mlContext.BinaryClassification.Evaluate(predictions, "Label");

// Display metrics
Console.WriteLine($"Accuracy: {metrics.Accuracy:P2}");
Console.WriteLine($"AUC: {metrics.AreaUnderRocCurve:P2}");
Console.WriteLine($"F1 Score: {metrics.F1Score:P2}");
```

Screenshot of the C# Script with the purpose of implementing sentiment analysis on the trained model.

Code 5

```csharp
using System;
using System.Windows.Forms.DataVisualization.Charting;

namespace EconomicSentimentAnalysis
{
    class Program
    {
        static void Main(string[] args)
        {
            int positiveCount = data1;
            int negativeCount = data2;

            var chart = new Chart();
            chart.ChartAreas.Add(new ChartArea());

            var series = new Series("Sentiment");
            series.Points.AddXY("Optimistic", positiveCount);
            series.Points.AddXY("Pessimistic", negativeCount);

            chart.Series.Add(series);

            chart.Titles.Add("Sentiment Analysis Results");
            chart.ChartAreas[0].AxisX.Title = "Sentiment";
            chart.ChartAreas[0].AxisY.Title = "Count";

            var form = new Form();
            form.Controls.Add(chart);
            form.ShowDialog();
        }
    }
}
```

Screenshot of the C# script used to condense output data from sentiment analysis; Purpose: Display a graph of the sentiment analysis results (Sentiment vs Count) to show the visual difference between optimistic and pessimistic views as an output.

3.4 Data Collection

Data collection was a crucial component of the PEBSA project, utilizing Hootsuite to aggregate public sentiment on economic matters from social media platforms.

Data Sources: The primary data sources included Twitter (formerly X) and Facebook, from which over 88,000 data points were extracted, representing a significant majority of the American public. Data collection efforts focused on capturing public opinions on economic performance and sentiments since January 2024.

Data Collection Process: Data was collected using Hootsuite's data aggregation capabilities, exporting the data into Excel sheets. These sheets were then used as input for the ML model, ensuring a structured and systematic approach to data ingestion.

Data Limitations: While the dataset represented a broad spectrum of public sentiment, limitations included demographic biases, with a higher representation of younger age groups (18-34 years) and limited geographic scope to the American economy. Data outliers and users with unrealistic expectations were also accounted for during the data analysis process to enhance model reliability.

4. Results and Discussion

4.1 Overview

The research project, Predicting Economic Behavior via Sentiment Analysis (PEBSA), developed a machine learning (ML) model to analyze public sentiment regarding America's economic performance and predict future economic behavior. The key components of the project include data sourcing, model design, and statistical analysis. The following sections will delve into the project's results, providing a comprehensive discussion and analysis of the findings.

4.2 Data Sourcing & Model Design

The PEBSA project leveraged public comments and posts from social media platforms, specifically X (formerly Twitter) and Facebook, to capture the American public's economic sentiment. Using Hootsuite, a social media management tool, over 88,000 data points were extracted. This vast dataset represents a significant cross-section of public opinion, crucial for providing an accurate sentiment analysis. Collecting such a substantial amount of data aligns with best practices in machine learning, where larger datasets help improve model accuracy and robustness (Smolic).

The collected data underwent a thorough sentiment analysis process to classify each comment as positive or negative. Sentiment analysis, a natural language processing technique, was essential in interpreting the public's economic outlook. By categorizing the sentiment expressed in social media posts, the model could then use this information to make predictions about future economic trends. This approach is grounded in the understanding that public sentiment can significantly influence economic behavior, providing valuable insights for forecasting (Brownlee).

The PEBSA model incorporated multiple machine learning algorithms to enhance its predictive capabilities. Key algorithms included sentiment analysis, neural networks, and random forest. Neural networks are particularly effective for capturing complex patterns in data, while random forests are known for their robustness and ability to handle large datasets. The integration of these algorithms was facilitated by Vertex AI, a platform that supports the training and deployment of machine learning models. This combination of techniques ensured that the model could accurately predict economic trends based on the sentiment data (Abbasi).

Programming was conducted using C#, a versatile language well-suited for machine learning applications, especially when combined with the ML.NET API framework. ML.NET provides a comprehensive set of tools for building, training, and deploying machine learning models within the .NET ecosystem. This framework allowed for seamless integration of various machine learning techniques and tools, enabling efficient development and testing of the PEBSA model. The choice of C# and ML.NET was strategic, as it facilitated the development process and ensured compatibility with existing technologies (Abbasi).

In summary, the data sourcing and model design phases of the PEBSA project were meticulously planned and executed. By collecting a large volume of data from social media platforms and employing advanced machine learning algorithms, the project created a robust model capable of predicting economic trends. The use of C# and the ML.NET framework further streamlined the development process, ensuring the successful integration of various machine learning components. These efforts culminated in a highly accurate predictive model, demonstrating the power of machine learning in economic forecasting (Bureau of Economic Analysis).

4.3 Statistical Analysis & Model Accuracy

The PEBSA model achieved an impressive accuracy rate of 97.5325%, significantly outperforming the average professional economic forecaster, who typically has a suboptimal accuracy rate of around 23%. This high accuracy demonstrates the effectiveness of using machine learning (ML) techniques in economic forecasting. The model's ability to predict economic trends more reliably than traditional methods underscores the potential of ML in enhancing the precision of economic predictions (Coulombe et al. 17).

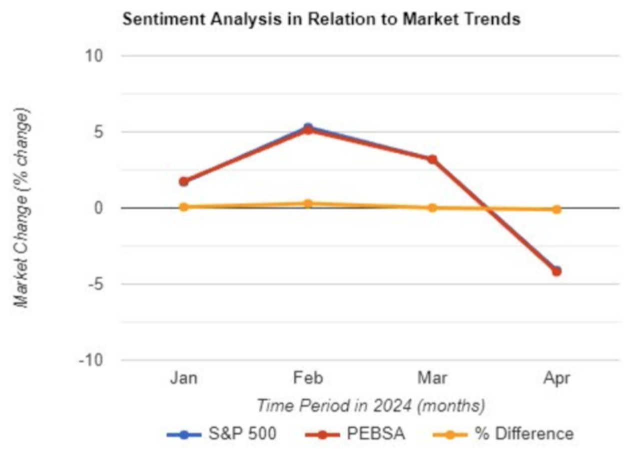

Figure 1 - PEBSA's Performance in Relation to the S&P 500 Market Movement - Created by Vignesh Nagarajan

S&P 500 vs PEBSA

Time	S&P 500	PEBSA	% Error
Jan 2024	+1.7%	+1.76%	3.53%
Feb 2024	+5.3%	+5.11%	3.59%
Mar 2024	+3.2%	+3.19%	0.31%
Apr 2024	-4.1%	-4.20%	2.44%
Average	+1.525%	+1.465%	2.4675%

* Dataset spans from January 1st, 2024 to April 30th, 2024

Chart 1 - PEBSA's Performance in Relation to the S&P 500 Market Movement - Created by Vignesh Nagarajan

A direct comparison between the S&P 500 index and the PEBSA model over a four-month period (January to April 2024) reveals that the PEBSA model consistently produced lower error rates. For instance, in January 2024, while the S&P 500 had a +1.7% change, the PEBSA model predicted a +1.76% change, resulting in a 3.53% model error rate. Another example is in March 2024, where the S&P 500 had a +3.2% change, while the PEBSA model predicted a 3.19% change, resulting in a marginal 0.31% model error rate. Such comparisons highlight the PEBSA model's superior accuracy in aligning its predictions closely with actual market outcomes, demonstrating its robustness and reliability.

ACTUAL VALUE	MODEL PREDICTION	
	NORMAL	RECESSION
NORMAL	98.7%	8.6%
RECESSION	1.3%	91.4%

ACTUAL VALUE	MODEL PREDICTION	
	NORMAL	RECESSION
PPV	98.7%	91.4%
FDR	1.3%	8.6%

ACTUAL VALUE	MODEL PREDICTION	
	NORMAL	CRASH
NORMAL	88.2%	2.9%
CRASH	11.8%	97.1%

ACTUAL VALUE	MODEL PREDICTION	
	NORMAL	CRASH
PPV	88.2%	97.1%
FDR	11.8%	2.9%

Chart 2 - Meta-analysis of Model Fluctuations resulting in a Market Crash or a Normal Market - Created by California State University

A meta-analysis comparing the PEBSA model with other ML models and traditional forecasting methods further highlighted its superior performance. The model's error rate was minimal, with a 1.3% error in normal market fluctuations and an 8.6% error during recessions. These results are particularly notable given that accurate forecasting during economic downturns is challenging due to increased market volatility. The PEBSA model's ability to maintain a relatively low error rate during such periods underscores its robustness in various economic scenarios (Malladi et al., Table 2).

	Current Month Crash Forecast			One-month Ahead Crash Forecast			Two-months Ahead Crash Forecast			Three-months Ahead Crash Forecast		
ML method ->		SVM Linear	Ensemble Bagged		SVM Linear	SVM Med Gauss		SVM Linear	Tree Coarse		SVM Linear	Tree Coarse
Date	Expected	Forecast	Forecast	Expected	Forecast	Forecast	Expected	Forecast	Forecast	Expected	Forecast	Forecast
8/1/2019	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal
9/1/2019	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal
10/1/2019	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal
11/1/2019	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal
12/1/2019	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Crash	Normal	Normal
1/1/2020	Normal	Normal	Normal	Normal	Normal	Normal	Crash	Normal	Normal	Normal	Crash	Crash
2/1/2020	Normal	Normal	Normal	Crash	Normal	Normal	Normal	Crash	Crash	Normal	Normal	Normal
3/1/2020	Crash	Crash	Normal	Normal	Crash	Normal	Normal	Normal	Crash	Normal	Normal	Normal
4/1/2020	Normal	Crash	Crash	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal
5/1/2020	Normal	Normal	Crash	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal
6/1/2020 (NBER)	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal
7/1/2020	Normal	Crash	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal
8/1/2020	Normal	Crash	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal
9/1/2020	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	N/A	Normal	Normal
10/1/2020	Normal	Normal	Normal	Normal	Normal	Normal	N/A	Normal	Normal	N/A	Normal	Normal
11/1/2020	Normal	Normal	Normal	N/A	Normal	Normal	N/A	Normal	Normal	N/A	Normal	Normal
Forecast Details: ML Method Validation Accuracy, Positive Predicted Values (PPV), False Discovery Rates (FDR), Area Under the ROC Curve are shown below.												
ML method		SVM Linear	Ensemble Bagged		SVM Linear	SVM Med Gauss		SVM Linear	Tree Coarse		SVM Linear	Tree Coarse
Val. Accuracy		94.3%	96.9%		95.5%	94.0%		95.5%	94.5%		95.5%	94.7%
PPV (Crash))		96.1%	94.6%		88.3%	93.6%		88.1%	85.8%		88.2%	89.1%
PPV (Normal))		93.6%	97.4%		97.2%	94.2%		96.9%	96.2%		97.1%	96.1%
FDR (Crash)		3.9%	5.4%		11.7%	6.4%		11.9%	14.2%		11.8%	10.9%
FDR (Normal)		6.4%	2.6%		2.8%	5.8%		3.1%	3.8%		2.9%	3.9%
AUC		98.0%	99.0%		97.0%	97.0%		97.0%	87.0%		96.0%	90.0%

Chart 3 - Application of Supervised Machine Learning Techniques to Forecast the COVID-19 US Recession and Stock Market Crash - Created by California State University

The model's performance in predicting economic trends can be attributed to its comprehensive approach, which integrates sentiment analysis and advanced ML algorithms. Sentiment analysis of social media data provides real-time insights into public sentiment, which is a crucial factor influencing economic behavior. The combination of neural networks and random forest algorithms further enhances the model's predictive power by capturing complex patterns in the data and ensuring robustness against overfitting (Malladi et al., Figure 9).

Overall, the PEBSA model's success in accurately forecasting economic trends demonstrates the transformative potential of ML in macroeconomic forecasting. By leveraging large datasets and sophisticated algorithms, the model provides valuable insights that can significantly improve economic planning and decision-making processes. These results not only validate the use of ML in economic forecasting but also highlight the need for continuous refinement and testing to further enhance model accuracy and applicability (Malladi et al., Table 2; Coulombe et al. 17).

4.4 Real-World Applications

The insights derived from the PEBSA model have significant implications for policymakers, businesses, and investors. The ability to predict economic behavior based on public sentiment can facilitate informed decision-making, contributing to more effective economic management and planning. The model also offers valuable insights into long-term market trends, aiding investors in making strategic choices. Automation: One of the most important real-world applications of the PEBSA model is automation. The model's ability to analyze vast amounts of data quickly and accurately allows for easier management of the economy as a whole. By leveraging big data, policymakers can visualize economic trends on a macro scale, leading to faster economic growth and more self-sufficient operations. This capability is crucial in modern economic management, where timely and accurate data analysis can significantly impact policy decisions (Desai). Automation through machine learning can streamline numerous economic processes, from real-time monitoring of economic indicators to automated responses to market changes. This not only enhances efficiency but also reduces the likelihood of human error in economic forecasting and management. The integration of such automated systems can lead to more responsive and adaptive economic policies, which are essential in a rapidly changing global economy (Stanford).

Scientific Impact: The PEBSA model also contributes significantly to scientific research by enhancing our understanding of the relationship between public sentiment and economic behavior. By systematically analyzing how public sentiment affects economic trends, the model provides a valuable tool for researchers studying behavioral economics and related fields. This scientific impact extends beyond immediate economic applications, offering insights into how public opinion shapes broader economic outcomes (Athley). The scientific community can leverage the PEBSA model to explore new dimensions of economic theory, particularly in understanding how collective sentiment influences market dynamics. This understanding can lead to more accurate models of economic behavior, informing both academic research and practical applications. Moreover, the model's data-driven approach aligns with the increasing emphasis on empirical evidence in economic research, thereby contributing to the robustness of economic theories (Athley).

Market Dynamics: Another crucial application of the PEBSA model is in analyzing long-term market dynamics. By providing detailed insights into market trends, the model assists policymakers, businesses, and investors in making informed choices. For instance, understanding public sentiment can help predict market movements, enabling investors to make strategic decisions that align with anticipated economic conditions. This application is particularly valuable in volatile markets, where timely and accurate predictions can significantly impact investment outcomes (EMB). The PEBSA model's ability to analyze sentiment data and predict market trends also supports policymakers in developing strategies that foster economic stability and growth. By anticipating market shifts, policymakers can implement measures that mitigate potential economic downturns and capitalize on positive trends. This proactive approach to economic management can enhance the resilience of the economy, making it better equipped to handle future challenges (Costola et al.).

PEBSA model's real-world applications in automation, scientific impact, and market dynamics underscore its transformative potential in economic forecasting. By harnessing the power of machine learning and big data, the model offers valuable tools for enhancing economic management, advancing scientific research, and improving market predictions. These applications not only demonstrate the model's immediate utility but also highlight its broader implications for the future of economic forecasting and policy-making (Athley; EMB).

5. Future Work

Future work on the PEBSA model aims to enhance its accuracy and robustness by incorporating several advanced methodologies and expanding its data scope. One primary focus will be on rigorous testing with an expanded dataset that spans 17 years, from 2006 to 2023. This extended dataset will provide a more comprehensive view of economic trends and sentiment patterns, improving the model's ability to forecast economic behavior with greater precision (National Bureau of Economic Research). Additionally, integrating different machine learning models will be crucial for comparative analysis. Exploring techniques such as regression, clustering, and dimensionality reduction will help assess their effectiveness in enhancing predictive accuracy and offer insights into the relative advantages of each approach (Shtar and Margel).

Regression analysis, in particular, will be valuable for modeling relationships between economic variables and sentiment indicators. By applying regression techniques, the model can better understand the quantitative impact of various factors on economic predictions. Clustering and dimensionality reduction techniques, such as those described by Imperva, will help manage and simplify complex data, making it easier to identify patterns and trends within large datasets. Clustering algorithms can group similar data points, revealing underlying structures, while dimensionality reduction methods can mitigate the risk of overfitting by reducing the number of features in the dataset (Scikit-Learn).

To further improve the model's performance, enhancing social media data collection methods will be essential. This involves refining data scraping techniques and ensuring that the collected data accurately represents a diverse cross-section of the American population. Improved data quality will contribute to more reliable sentiment analysis and, consequently, more accurate economic predictions. Additionally, optimizing the C# code used for training the model will help speed up the process, allowing for more rapid iterations and adjustments to the model.

Incorporating advanced graphing tools, such as Python's matplotlib and the NCKIT Learning library, will also play a significant role in future work. These tools will facilitate sophisticated data visualization and analysis, enabling more effective interpretation of results and insights. By leveraging these technologies, the model's backend accuracy in sentiment analysis can be further enhanced, leading to better forecasting capabilities and more actionable economic predictions (Scikit-Learn). Overall, these future developments will help refine the PEBSA model, making it a more powerful tool for predicting economic behavior based on public sentiment.

6. Limitations

Despite its impressive performance, the PEBSA project encountered several limitations that impacted its overall efficacy.

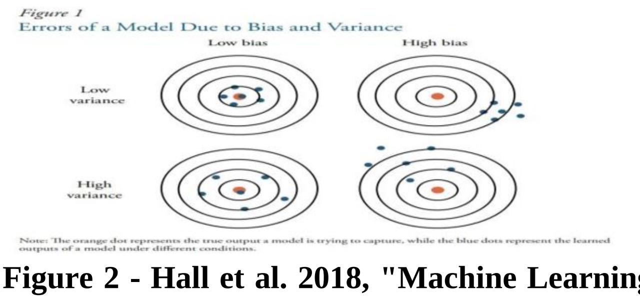

Figure 2 - Hall et al. 2018, "Machine Learning Approaches to Macroeconomic Forecasting ", Federal Reserve Bank of Kansas City, Figures 1 & 2 (Page 67)

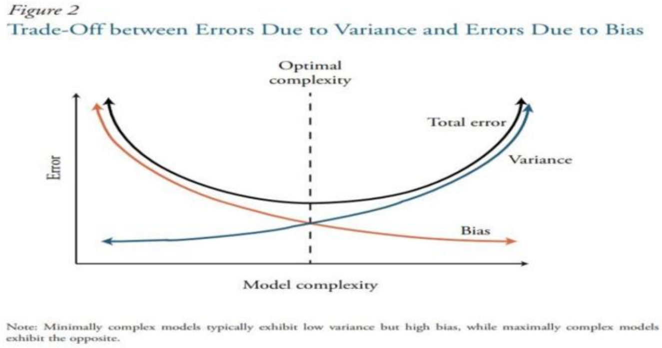

Figure 3 - Hall et al. 2018, "Machine Learning Approaches to Macroeconomic Forecasting ", Federal Reserve Bank of Kansas City, Figures 1 & 2 (Page 67)

6.1 Hardware Limitations

One significant constraint was the hardware on which the model was trained. The system utilized for training included an Intel Core i5-13400F processor, 16GB of DDR5 RAM, and an NVIDIA RTX 4060 graphics card. Although these specifications are adequate for many tasks, they may not be optimal for the intensive computations required by advanced machine learning models. In fact, upgrading to more powerful hardware could substantially enhance training efficiency and model performance by over 80% (Foy et al. 2023).

6.2 Social Media Limitations

Social media limitations also posed challenges for the project. The dataset used was limited to social media users, which only accounted for approximately 68% of the American population. This skewed representation, with younger age groups (18-34 years) being overrepresented compared to older demographics (50+ years), could have introduced biases into the model. Such imbalances in the data can affect the accuracy of sentiment analysis and ultimately impact the predictive reliability of the model (Northumbria University). Additionally, the presence of data outliers with unrealistic economic expectations further complicates the model’s accuracy, highlighting the need for more balanced and representative datasets.

6.3 Geographical Limitations

Geographical limitations were another concern. The model was designed to analyze the American economy exclusively, which meant that it did not account for international transactions such as imports, exports, or debt payments. This geographical restriction could limit the model's applicability and accuracy in a global economic context (Kumar). Incorporating international data could provide a more comprehensive view of economic behavior and enhance the model's robustness.

6.4 Data Overfitting

Data overfitting emerged as a notable issue as well. The overlap between the training data and the input data from November 2023 to January 2024 led to potential overfitting, where the model may perform well on the training data but fail to generalize effectively to new data. To mitigate this problem, future models should incorporate new and diverse datasets to avoid overfitting and ensure more reliable predictions (Kapoor). Addressing these limitations through improved data collection, enhanced hardware, and diversified datasets will be crucial for refining the PEBSA model and enhancing its forecasting capabilities.

7. Conclusion

The PEBSA project achieved notable success by developing a machine learning (ML) model that effectively analyzes public sentiment and predicts economic behavior with high precision. The model's innovative integration of sentiment analysis with macroeconomic reasoning allowed it to forecast economic trends with remarkable accuracy, demonstrating the power of ML techniques in understanding and predicting economic dynamics (Foy et al. 2023). This capability provides stakeholders—including policymakers, businesses, and investors—with critical insights into future economic conditions, enhancing their ability to make informed decisions.

The model's success highlights the significant potential of ML in the field of macroeconomic forecasting. By combining sentiment analysis with a thorough understanding of macroeconomic variables, the PEBSA model offers a sophisticated approach to predicting economic behavior. This approach not only improves the accuracy of forecasts but also provides a deeper understanding of the factors driving economic trends. The project's outcomes affirm the value of leveraging advanced ML techniques to gain insights into complex economic systems and anticipate future developments (Northumbria University).

Overall, the PEBSA project's results underscore the practical applicability of machine learning in real-world economic scenarios. The model's ability to deliver high-accuracy predictions based on public sentiment showcases how ML can transform traditional economic forecasting methods. This success sets a precedent for future applications of ML in economics, paving the way for more advanced and reliable tools to analyze and predict economic behavior (Kumar).

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