Predictive Analysis of Economic Vulnerability Using News Data

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Abstract - Economic vulnerability is a critical issue for policymakers, particularly in developing countries like the Philippines, where sector-specific risks require timely insights for proactive interventions. Traditional economic indicators sometimes lack real-time responsiveness and miss social shifts signaling emerging vulnerabilities. This study proposes using web-scraped news data to predict economic vulnerabilities by analyzing sentiment trends across key sectors—Agriculture, Manufacturing, and Finance. Sentiment analysis with FinBERT, tailored for economic contexts, assesses sector-specific vulnerabilities, while an LSTM model forecasts future sentiment trends from time-series data. This methodology offers an innovative, real-time approach to forecasting economic risks, particularly in data-scarce environments.

I. INTRODUCTION

A. Background of the Study

Economic vulnerability is a critical concern for policymakers, as it directly impacts a nation's ability to withstand and recover from economic shocks, ensuring long-term stability and sustainable development [1]. Traditionally, vulnerability assessments have relied on quantitative measures such as sectoral Gross Domestic Product (GDP) contributions, employment rates, inflation indices, and trade balances [2]. While these indicators are invaluable for understanding macroeconomic conditions, they sometimes lack the immediacy and contextual depth required to identify emerging risks [3]. Furthermore, conventional economic data is typically reported with delays due to the time-intensive processes involved in data collection, validation, and aggregation [4]. National statistical agencies and international organizations often require extensive verification and standardization to ensure data accuracy and consistency, which inadvertently results in lagging updates that hinder timely economic decision-making. These delays can hinder the timely formulation of interventions, worsening vulnerabilities before they are adequately addressed. In regions with limited access to infrastructure or in developing countries, where systematic data collection is often difficult or resource-intensive, these delays become even more pronounced. In such contexts, timely access to economic insights is essential to anticipate vulnerabilities and implement proactive measures.

Another limitation of traditional economic metrics is their inability to capture qualitative and contextual factors that influence economic stability, such as public sentiment, societal perceptions, and reactions to global events. Research indicates that intangible elements like consumer confidence and investor sentiment often serve as leading indicators of economic performance, particularly during periods of uncertainty [5]. However, such factors are sometimes neglected in conventional analyses, which focus primarily on quantifiable variables. This narrow perspective risks overlooking critical early signals of economic instability, especially in sectors sensitive to public opinion and external shocks, such as agriculture, finance, and manufacturing.

Real-time data sources, such as economic news, present a complementary approach to traditional metrics. News articles provide immediate, context-rich narratives that reflect societal responses, investor confidence, and public perceptions of ongoing economic developments [6]. Sentiment analysis has emerged as a powerful tool for extracting actionable insights from such data, with models like FinBERT offering robust capabilities in understanding sentiment in financial contexts. By applying sentiment analysis to news data, early contextual warnings of sectoral vulnerabilities can be identified, enabling a more nuanced understanding of emerging risks.

In addition to sentiment analysis, advancements in machine learning, particularly the use of Long Short-Term Memory (LSTM) networks for time-series forecasting, have revolutionized the ability to predict trends in dynamic and sequential data [7]. LSTMs, a specialized type of recurrent neural network, are particularly adept at capturing patterns in time-dependent data, making them well-suited for analyzing the evolution of sentiment trends over time. Integrating LSTM models with sentiment analysis offers a promising avenue for predicting shifts in economic sentiment, enabling a forward-looking perspective on economic vulnerabilities.

Despite these advancements, there remains a need to systematically apply these methodologies to address specific national contexts where sectoral vulnerabilities require timely and precise assessment. The collective usage of these tools and their application to real-world economic challenges highlights the gap in proactive, data-driven approaches to understanding and mitigating economic risks.

B. Problem Statement

Traditional economic indicators are essential for assessing the economic situation of a country, but they sometimes fail to capture real-time shifts in public sentiment and societal reactions, which may signal emerging vulnerabilities. These indicators are typically reported with delays due to time-intensive data collection and validation processes, a problem that is intensified in remote or underdeveloped regions where data gathering is challenging. Furthermore, these indicators primarily focus on quantifiable metrics, neglecting the contextual factors that can also impact economic stability.

While news data provides real-time insights into public sentiment and economic reactions, systematic methods for analyzing this data to predict economic vulnerabilities remain underdeveloped. This gap in research limits the ability to anticipate economic shifts or sectoral vulnerabilities in real time, especially in regions where the availability of conventional economic data is limited or delayed. Consequently, there is a critical need for methods that can effectively leverage news sentiment to provide early warnings of emerging economic risks.

C. Objectives of the Study

The primary objective of this study is to develop a reliable methodology for predicting economic vulnerabilities using news data, with a particular focus on identifying economic subsector-specific risks. Specifically, this research aims to:

1) Implement transfer learning techniques to classify news articles related to economic events into predefined vulnerability sectors, drawing on existing datasets from other countries.
2) Evaluate the sentiment of economic news articles within each sector to assess the vulnerability sentiment using the FinBERT sentiment analysis model.
3) Utilize LSTM networks to perform time-series analysis on sector-specific sentiment data, predicting future trends and identifying potential risks to economic stability.

D. Significance of the Study

This study introduces a novel approach to understanding economic vulnerability by utilizing news sentiment as a predictor of sector-specific risks. Unlike traditional economic indicators, which often suffer from delays in data collection and validation, this research offers a real-time, context-driven method for identifying and forecasting emerging vulnerabilities. By analyzing sentiment trends in economic news, this study enables the early identification of potential disruptions, providing policymakers with proactive insights before these issues are reflected in conventional economic metrics.

The study is designed both as an early insight tool when numerical data is unavailable or delayed, and as a complementary tool to enhance forecasts when such data is available. While not directly integrating sentiment analysis with traditional economic models, this research lays the foundation for future systems that combine both qualitative and quantitative data to support data-driven policy decisions. Ultimately, it aims to demonstrate the efficacy of news sentiment analysis in forecasting economic vulnerabilities and contributing to the development of integrated policy frameworks.

E. Scope and Limitations

This study focuses on the application of news sentiment analysis to predict economic vulnerabilities within predefined sectors in the Philippines. Specifically, it leverages sentiment derived from economic news articles to assess sector-specific risks, with the goal of providing early insights into emerging economic challenges. The study is primarily concerned with sentiment analysis and does not integrate traditional economic models. Additionally, the research is limited to the analysis of news articles and does not consider other forms of media, such as social media platforms, which may also contribute to shaping public sentiment. The scope is further restricted to the predefined vulnerability sectors, excluding other economic sectors that may also be at risk. Moreover, this study does not explore potential biases inherent in the news sources nor does it investigate the broader policy implications of incorporating sentiment analysis into economic forecasting. These considerations could be addressed in future research. Despite these limitations, the findings are potentially generalizable to other countries, particularly through the use of transfer learning techniques, which enable the adaptation of models trained on external datasets for local application.

II. REVIEW OF RELATED LITERATURE

1. Economic Vulnerability and its Assessment

A. Definition and Importance of Economic Vulnerability

Economic vulnerability refers to the susceptibility of an economy to shocks that can disrupt its stability, which can make it difficult for the economy to grow [8]. It is a threat that results from the complex interaction of societal factors and includes both intrinsic weaknesses and external risks. Intrinsic weaknesses are shortcomings that usually manifest in forms of overdependence on specific and volatile markets [9], while external risks are usually the factors that cannot be inherently controlled, such as natural disasters [10]. In essence, it highlights the degree to which an economy is exposed to potential harm and its capacity to absorb and recover from such adversities.

Understanding economic vulnerabilities is critical due to its significant implications for economic stability and policymaking [11]. Economic stability is sought because at times of instability, the economy may have unpredictable demand and supply chain disruptions while also negatively affecting purchasing power. Ultimately, an unstable economy makes it more difficult for people to access products essential for survival. Having the ability to identify the economic vulnerabilities correctly enables policymakers to design proactive measures to enhance resilience against these vulnerabilities. Furthermore, understanding these risks helps in making informed decisions about crisis management to ensure that resources are effectively allocated to mitigate potential disruptions. Moreover, there have already been studies which show that countries with robust mechanisms for monitoring economic vulnerabilities tend to maintain greater economic stability, even in the face of significant global challenges [12][13]. Finally, studies have also shown that nations with a clear identification and understanding of their vulnerabilities recover more rapidly from crises [14][15]. These findings highlight the importance of understanding economic vulnerabilities for adequate preparation and preemptive action to preserve economic stability, and in turn, to maintain the comfortable quality of life of the people.

B. Traditional Economic Indicators

Traditional economic indicators are metrics that rely on systematically collected measurable or numerical data [16]. They assess the different aspects of economic performance basing on multiple different sources and have been the cornerstone of economic assessments for decades. A commonly known traditional indicator is the Gross Domestic Product (GDP) which is the total monetary value of all goods and services produced by a country, typically measured quarterly or annually [17]. Although these metrics are widely used, these metrics sometimes fail to capture rapid and unpredictable economic changes due to their delay in reflecting the ongoing economic conditions [18]. Other metrics such as employment rates may not capture data from informal labor sectors, which are particularly relevant in developing economies. In general, these metrics also do not account for the reactive changes in consumer behavior or shifts in market sentiment on time that could foreshadow economic instability. However, having access to the most updated data is crucial for drawing insights that can help with the timely response in dealing with potential risks. Therefore, relying solely on these indicators can make it challenging to address vulnerabilities as they emerge.

C. Sector-Specific Vulnerabilities

Sector-specific vulnerabilities refer to the economic risks faced by individual sectors which are often influenced by both macroeconomic factors and sector-specific dynamics [19]. These vulnerabilities manifest uniquely based on their dependencies, with agriculture, manufacturing, and finance standing out as some of the most critical areas of concern due to their widespread impact based on the existing literature [20][21]. The agriculture sector is sensitive to natural disasters and sudden changes in climate which disrupt production and threaten food security, particularly for smallholder farmers in developing nations [22]. The manufacturing sector is an important part of industrialized economies. However, it faces challenges from rising energy costs and global supply chain disruptions, as seen during the COVID-19 pandemic [23]. Furthermore, the financial sector remains vulnerable to systemic risks, market confidence issues, and cybersecurity threats [24]. A single failure can start a cascading effect through the whole sector. Addressing sector-specific vulnerabilities require a targeted investment in resilience, diversification, and sustainable practices while drawing lessons from vulnerabilities in other sectors, such as technology, healthcare, and transportation.

2. Sentiment Analysis in Economic Applications

A. Sentiment Analysis Models in Economics

Sentiment analysis is a tool that enables one to extract insights from unstructured text data [25]. In the case of economics, unstructured data can be sourced from news articles and financial reports. Unlike traditional economic indicators that rely on quantitative data, sentiment analysis evaluates the qualitative aspects like consumer confidence, and investor sentiment.

FinBERT is a transformer-based sentiment analysis model fine-tuned on financial texts [26]. FinBERT outperforms generic sentiment analysis models, having accuracies ranging from 86% to 97% on benchmark datasets. The inclusion of economic-specific lexicons and embeddings enhances the interpretability and precision of this model, making it ideal for assessing vulnerabilities.

Literature reveals that sentiment analysis models are highly effective in identifying early economic signals, even before they are shown traditional indicators [27]. Moreover, integrating sentiment analysis with traditional econometric methods provides a complementary framework for understanding economic shifts [28]. Policymakers and economists increasingly rely on these insights to design adaptive strategies, especially during periods of economic uncertainty.

The effectiveness of sentiment analysis in economics highlights its transformative potential. Real-time analysis enables the identification of trends and vulnerabilities before they manifest in traditional indicators. By offering high accuracy and domain specificity, these models contribute to responsive economic planning and informed decision-making.

B. Sentiment Analysis as an Early Warning System

Sentiment analysis has increasingly been employed as an early warning system in economics, especially in detecting shifts in economic trends that are not yet visible in traditional data [29]. Studies have demonstrated that sentiment trends in news articles and financial reports can serve as leading indicators of economic shifts [30]. To illustrate, one study found that a sudden increase in negative sentiment within financial markets often precedes a decline in stock prices and can signal broader economic downturns [31]. By identifying changes in sentiment before they are reflected in hard data, policymakers and investors can anticipate risks and take timely actions to mitigate negative outcomes. The predictive power of sentiment analysis is particularly valuable during times of crisis, where traditional economic indicators may not be updated enough to indicate currently emerging threats. In connection to that, a study found that sentiment analysis of news and twitter data related to a natural disaster or geopolitical conflict can provide early warnings of economic distress, allowing governments and businesses to implement mitigation strategies before the full economic impact becomes apparent [32]. This ability to identify potential economic shocks early makes sentiment analysis a critical tool for economic forecasting and risk management.

III. Machine Learning Techniques for Economic Forecasting

A. Transfer Learning in NLP for Economic News

Transfer learning involves fine-tuning pre-trained models on domain-specific data to apply knowledge learned from one domain to another [33]. It allows for the application of general language models to more specialized tasks like understanding economic trends or sector vulnerabilities. This approach is particularly beneficial in scenarios where labeled data is scarce and where limited training data might otherwise hinder accurate sentiment classification or trend forecasting [34]. One useful scenario is when there is no available annotated news data from a specific country, so a model trained on the news data of another country can be used as a fast and effective way of acquiring results for the lacking country without loss of generality [35].

B. LSTM for Time-Series Forecasting

Long Short-Term Memory (LSTM) network is a type of recurrent neural network (RNN) that is well-suited for sequential data because they can capture long-range dependencies and trends in time-series data [36]. It outperforms traditional time-series methods because of its ability to process both short-term fluctuations and long-term patterns [37]. It has demonstrated considerable potential in economic forecasting, having been successfully applied in various economic forecasting tasks, including predicting stock market movements, foreign exchange rates, and even commodity prices [38]. This model is particularly useful when historical data is abundant, allowing for accurate trend predictions that can inform policymaking and strategic decisions. Moreover, its ability to model complex, nonlinear relationships between economic indicators makes LSTM networks a viable option for predicting shifts in economic conditions that traditional statistical methods might not fully capture.

C. Sentiment-Driven Forecasting

Sentiment-driven forecasting integrates sentiment analysis with time-series forecasting models allowing for more nuanced predictions of economic shifts [39]. This hybrid approach uses sentiment data extracted from news articles or financial reports to predict future economic trends and vulnerabilities. By incorporating sentiment signals, such models can account for investor behavior and public perception, which often precede shifts in traditional economic indicators. The synergy between sentiment and time-series data enables models to predict risks and overall economic instability, offering earlier and more actionable insights than traditional forecasting techniques.

Studies have demonstrated the efficacy of sentiment-driven forecasting models in various domains, such as stock market predictions and financial stability assessments [40] [41]. By combining sentiment data with time-series forecasting, these models are able to incorporate both quantitative economic indicators and qualitative sentiment signals to forecast market behavior more accurately. For instance, incorporating sentiment trends from financial news can improve the accuracy of stock price predictions, offering insights into market trends that would otherwise be difficult to detect with numerical data alone [42]. These approaches are especially valuable in sectors with high volatility, where sentiment shifts can quickly lead to economic disruptions.

III. MATERIALS AND METHODS

This section will discuss how insights will be drawn to forecast economic vulnerabilities from economic news data. Only news data from the Philippines will be used since it is the country where the authors reside, enhancing the context and familiarity to enable better analysis. All procedures will be done on Python 3.11.9 on an ASUS TUF Dash F15 with a 12th Gen Intel Core i5-12450H 2.00 GHz processor and 8.00 GB RAM. The modules and libraries used will be discussed in specific sections. There will be four sections, mainly data collection, sector classification, sentiment analysis, and time series forecasting.

A. Data Collection

Economic news data will be gathered using the BeautifulSoup library from the following reliable local sources: Philippine Daily Inquirer, Philippine Star, Manila Bulletin, ABS-CBN, and Rappler. The target is to collect approximately one news article per day per sector over a period of two years from 2021 to 2023. The scraping process will include the pandas library for structuring the data and dateparser to standardize publication dates. The collected data will be stored as a Microsoft Excel file.

B. Sector Classification

News articles will be classified into one of three predefined economic sectors: Agriculture, Manufacturing, or Finance. Transfer learning will be applied using the RoBERTa model from the list of Hugging Face Transformers. It will be fine-tuned on labeled economic news datasets from other countries sourced from publicly available repositories in Kaggle. Datasets from comparable economies will be adapted, and the performance of the fine-tuned model will be validated manually and using accuracy, precision, recall, and F1-score as metrics and implemented with the Scikit-learn module. The implementation will use PyTorch with GPU acceleration for efficient training.

C. Sentiment Analysis

Sentiment analysis will determine the vulnerability sentiment of news articles within each economic sector. The FinBERT model will be utilized to assign numerical sentiment scores to each article. Text preprocessing will involve SpaCy for tokenization, lemmatization, and stop word removal, ensuring compatibility with FinBERT. Sentiment scores will be aggregated monthly to create a time-series dataset for each sector and will be stored in a Microsoft Excel file for subsequent time-series analysis.

D. Time-Series Forecasting

Sentiment scores aggregated per month for each sector will be structured into time-series datasets, organized using Pandas. Keras with a TensorFlow backend will be used to implement a Long Short-Term Memory (LSTM) network to predict future sentiment trends for each sector. The LSTM model will be trained and evaluated using historical sentiment data. To evaluate the robustness of the model, the data will be split into a training and testing set using a train-test split approach, ensuring that the training data consists of the first 1.5 years, with the last six months reserved for testing.

Cross-validation will be employed using the rolling cross-validation (rCV) method to ensure that the model generalizes well across different temporal segments. The Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) will be the performance metrics used to ensure predictive accuracy. Visualizations of predicted trends will be created using Matplotlib to support interpretability.

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