Technical Journal, University of Engineering and Technology (UET) Taxila, Pakistan Vol. 29 No. 2-2024
ISSN:1813-1786 (Print) 2313-7770 (Online)

Smart Growth Predictions: Deep Learning Applications in Economic Forecasting

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Abstract- Forecasting economic growth of countries is a complex and challenging task, but it has the potential to provide valuable insights for policymakers, investors, and businesses. Several AI based techniques have been used in various time series forecasting applications, including economic growth prediction. This paper explores the potential of Deep Learning (DL) techniques to enhance the accuracy of forecasting by extensively examining data from the CEIC Data Global Database. It focuses on key economic indicators such as Gross Domestic Product (GDP) growth, inflation, unemployment etc. across 50 countries, grouped into five regions, over the past 20 years. The proposed DNN model is developed in python using Keras / TensorFlow, trained for 200 epochs via Adam optimization and MAE loss to optimize model parameters by making 2000 full passes over the training data. The DL model forecasts Asia achieving the highest GDP growth rate amongst the continents through the period, followed by North America, Europe, and others.

Keywords- Economic Forecasting, Machine Learning, CEIC Database, Growth Prediction, Deep Learning, Data Mining, Data Analytics, Predictive Modeling, Artificial Intelligence.

I. INTRODUCTION

The GDP functions as a singular and comprehensive indicator for analyzing the economic tendencies of any nation [1]. It includes the overall value of goods and services produced within the economy [2]. GDP growth serves as the widely adopted indicator for assessing economic expansion within a nation. Conceptually, GDP represents the combined monetary value of all goods and services produced domestically during a specified timeframe [3]. Economists measure GDP using three interconnected methods based on the accounting approach [4]. The first method, known as the production approach, aggregates the value-added at each production stage, incorporating net government taxes and public subsidies. The second method, the income approach, encompasses factor income generated from production, including employee remuneration, capital income, business profits, taxes on production, and imports minus subsidies. The third method, the expenditure approach, calculates the combined expenditures of households, businesses, and governments on goods and services, along with net exports. From a mathematician perspective, it generally entails the summation of consumption, investment, government spending, and net exports [5]. This calculation offers understanding into both the comprehensive scale and expansion of an economy however it does have constraints. For instance, it does not consider quality of life, income distribution or other environmental factors. Beside these issues, timely detections of economic decline are another challenge for policy makers, which in turns leads to imprecisions due to inadequate understanding of the current economic state. Spotting a drop in financial yield at an appropriate time would empower policy makers to make suitable amendments in both financial and fiscal policies, targeting to prevent a recession or mitigate its impact on the real economy. Current approaches frequently lack the competence to promptly and effectively predict the onset of a downturn. Academics, investors, and regulators view GDP [6] as a representation of the economy's wealth and a significant indicator influencing decision-making processes. Consequently, forecasting GDP becomes a crucial matter, as it not only informs national economic policies but also finds relevance in various other domains, ranging from managing non-performing loans to handling natural disasters. Predicting the economic growth of countries can provide invaluable insights to governments, investors, and businesses [7-8].

Artificial Intelligence (AI) and various Machine Learning (ML) methodologies assume a pivotal role in such a scenario, offering the opportunity to supervise complex economic systems enriched by widespread datasets [9]. The emergence of advanced AI systems has enhanced an organization's capacity to utilize data for predictive purposes and significantly diminished the expenses associated with making such predictions. AI holds the top position among strategic technologies as per Gartner's technology trend survey in 2018 [10].

Harnessing AI may enhance decision-making process, reform business structures and ecosystems, and revolutionize the customer experience. Around 59% of organizations are in the process of accumulating insights to formulate their AI approaches, whereas the remaining segment has at present progressively integrating AI solutions. ML stands as an important method for building models capable of establishing connections across varied economic data sources and adaptively addressing varied challenges without dependence on human intervention [11].

This research work implements and evaluates a predictive model for GDP fluctuations, employing DL techniques. This proposed technique can forecast the economic growth of 50 countries grouped into five regions using 20 years of historical economic data from the CEIC Data Global Database [12-13]. CEIC Database is a comprehensive online database covering more than 200 countries with over 3 million economic indicators ranging from GDP growth to stock prices [14]. For this analysis, quarterly data on GDP growth, inflation, unemployment rates, and other factors from 1998 to 2018 for 50 countries were extracted from the database. A deep neural network (DNN) was trained on 80% of this data and used to predict GDP growth for the next 8 quarters for each country. The contemplated literature review for this research is hereafter for the betterment of Data Mining (DM) for economics intelligence [15].

II. Literature Review

To retain rapid insight on economic tendencies, there are numerous schools of thoughts about economic mechanisms and variables to be analyzed. In view of topical crises in the global economy, the issue of projecting GDP is highly deliberated. The existing work on GDP growth forecasting has mainly focused on developed economies, with limited evidence on emerging countries. Earlier studies have used numerous statistical methods, such as vector autoregressions and Bayesian vector autoregressions, to predict macroeconomic and financial variables.

The study presented by Nyman and Ormerod [16], focuses on short-term prediction of factual GDP progression for United Kingdom and United States together with a statistical tactic by using Ordinary Random Forest (RF) and Least Squares (OLS) regression. The study investigates the effectiveness of these techniques as an early warning system for recessions. Using a limited set of explanatory variables from financial markets available during the forecast period, the algorithm is trained and makes predictions at intervals of one, three, and six quarters ahead. J. Roush, K. Siopes and G. Hu [17] used autoregressive models to construct a vector to predict GDP. The forecasted outcome aligns with historical GDP data and anticipates a steady pattern of future growth. The limitation of this technique was that it was not able to overcome historic economic recession and the approach did not consider parameters such as trade, economic, geographical to predict the GDP growth. Onu, Ezemagu and Oden [18], demonstrated the effectiveness of principal component regression in increasing the accuracy of GDP forecasts when compared to conventional statistical methods. Mullainathan, Sendhil, and Jann Spiess [19] presents a viewpoint on ML that creates its distinct position within the econometric toolbox. ML not only introduces novel tools but addresses a distinct challenge, especially prediction, while numerous economic applications primarily focus on parameter estimation. Vaishnavi Padmawar, Pradnya Pawar, and Akshit Karande [20] predicted GDP by means of linear regression and random forest. The "Random Forest" used in this research proved efficiency with an 86% precision rate. Though, there is room for improvement in this model by using advanced ML algorithms to improve accuracy more. Adam Richardson, Thomas van Florenstein Mulder and Tugrul Vehbi [21], investigated the potential of ML algorithms to enhance current forecasts of real GDP growth in New Zealand. Their analysis involved a wide-ranging real-time dataset including around 550 macroeconomic indicators from both New Zealand and international sources. The ML algorithms exceed the performance of the statistical benchmarks. Moreover, incorporating the nowcasts from the ML models results in further enhancements in performance. Kouziokas, G.N. [22], employed Feedforward Multilayer Perceptron (FFMLP) for time series forecasting. To build the optimal forecasting model, numerous network topologies were explored by testing with diverse transfer functions and changing the number of neurons in the hidden layers. The results confirmed extremely accurate forecasts, mainly in predicting GDP levels. The proposed ML technique holds great prospective for applications in public and financial management. Tanveer Ahmad in [23] apply quantum computing and deep learning methods to construct new GDP growth forecasting models and compare their accuracy, using a sample of 70 countries (47 emerging and 23 developed).

III. Methodology

The paper presents a novel methodology for forecasting GDP that differs from traditional econometric methods. The proposed approach harnessing the abilities of DL techniques to improve the precision of GDP predictions. The data employed for this research was sourced from the CEIC Data Global Database repository,

encompassing a diverse set of economic indicators. This research adopted the Cross-Industry Standard Process for DM (CRISP-DM) as shown in Figure 1, generally recognized as a structured framework for the several stages of DM, including tasks such as data collection, data preparation, model building, and evaluation. Through combining the DL approach, diverse economic indicators, and the structured CRISP-DM methodology, this research contribute to the development of accurate and reliable GDP forecasting models, proposing insights into economic dynamics on a global scale.
The proposed methodology offers a useful summary of the key areas and methods of data analytics. The highest level is data science, which draws information and insights from data using scientific methods, systems, and processes as shown in Figure 2. Several fundamental fields make up data science, including:

- ML focuses on utilizing algorithms to automatically learn from and forecast data. Techniques for supervised and unsupervised learning are demonstrated. The field of developing computers and systems that can think and behave intelligently like humans is known as AI. This uses various techniques, including ML.
- DM is the process of applying particular algorithms to massive datasets to extract patterns. The diagram shows both structured and unstructured data sources.
- DL demonstrates the potential of ML models like neural networks. DL demonstrates how ML models, such as neural networks, can include numerous layers to gradually extract more complex features from raw data.

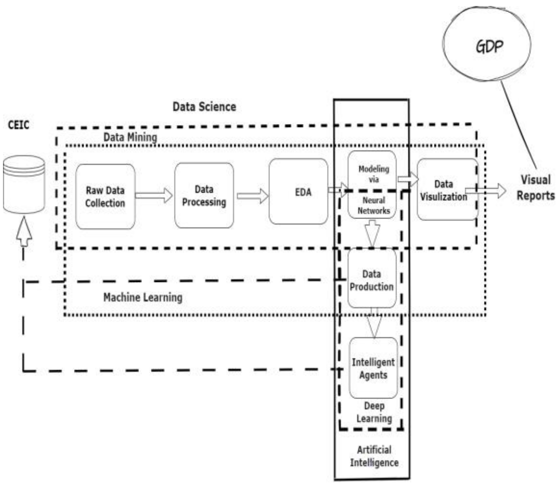

Figure 1. Methodology implementation by correlating various technologies

Recapitulate the facts provides the newness from the old dataset, giving data science a comprehensive picture of the field by demonstrating the connections and interdependencies between ML, DL, DM, and AI. Figure 1 explains the key distinctions and connections between these important subjects within the context of data science.

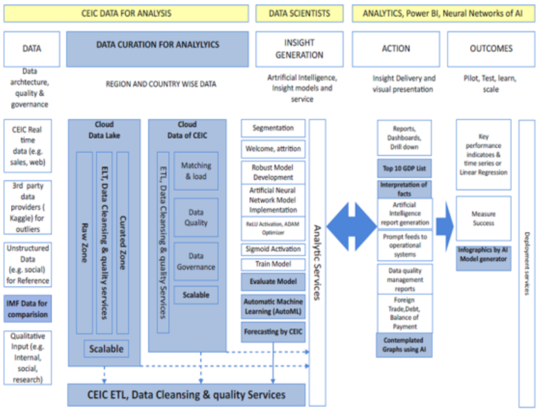

Figure 2. Architectural Diagram in terms of ANN

This study aimed to develop a robust neural network model for predicting GDP growth using CEIC macroeconomic data. The CEIC dataset was initially loaded and preprocessed, involving handling of missing values, encoding categories, and normalization. The processed data was then split into training, validation and testing sets. Various neural network architectures were defined and evaluated. Specifically, models using sigmoid activations for hidden layers and ReLU for the output layer were compiled and trained on the CEIC training data. The losses and accuracies on the validation set were examined during training to avoid overfitting. Additionally, the process was repeated using solely ReLU activations for comparison purposes. Upon completion of training, the most promising models as determined by the validation set were then evaluated on the held-out test data. This selection process identified the best performing model for making predictions on new, unseen data. Finally, the selected model was used to predict GDP growth values for additional countries, demonstrating its capability for forecasting purposes.

A. Data Collection and Preprocessing

Data on GDP growth, inflation, unemployment rates, and other economic factors were downloaded from the CEIC Database as.csv files and preprocessed to remove incomplete records. The data was split sequentially into training and test sets, with the final 20% of the data as the test set. The training data was used to build and optimize the DL model. CEIC provides a comprehensive, high-quality, up-to-date, and easy-to-use collection of economic data and statistics that is invaluable for research, analysis, forecasting, policymaking, and gaining key insights. The wide usage and aggregate indicators also make it very valuable. Overall, CEIC is an important resource for progress in economics and key to development. The Cornell University Library estimates that the CEIC dataset, which uses a variety of time-series methods to analyze data from more than fifty nations, is roughly 1.2 million records large [24]. Table 1 illustrates the steps involved in preparing the data for the proposed model.

Table 1. Data curations phases during data collection and preprocessing phase

Missing Data Imputation	• CIEC adopts the following methods to overcome the missing data issue. • Identification of Missing Data by time stamp, Determining Imputation Method, Imputation by Region/Country Group, Temporal Interpolation, Imputation by Correlated Variables, Plausibility Checks, Marking Imputed Data, Updating with New Source Data, etc. • Depending on the kind of variable (continuous vs. categorical), simple imputation techniques like mean and median are employed to replace missing values.
Data Transformation	• Text descriptors and other non-numeric variables are transformed into numeric codes. • Values reported in various units (such as thousands and millions) are converted to a single unit for normalization.
Outlier Treatment	• The interquartile range rule is used to identify probable outliers (IQR values greater than 1.5 from Q1/Q3). • Outliers (-3 or >3 standard deviations) are confirmed using statistical tests like z-scores. • If outliers are discovered to be errors, they are investigated, fixed, or eliminated
Checks for Consistency and Plausibility	• Data is periodically examined for logical inconsistencies. • Reverting to the original sources corrects improbable combinations.
Standardization	• Data is standardized to a common time period, time series, currency, etc.

The terms, explanations, and approaches are consistent. The huge integrated macroeconomic database maintained by CEIC benefits from these statistical data cleaning procedures to assure its consistency and quality. High-quality insights need to be powered by meticulous data management.

B. Model Development

A DNN was developed in Python using the Keras library with a Tensorflow backend. The model consisted of an input layer, three hidden layers with ReLU activations, and an output layer with linear activation. The model was trained for 200 epochs using the Adam optimizer and the mean absolute error loss function. An epoch refers to one full pass of the entire training dataset through the model. So, training for 200 epochs' means the model saw the entire training data 2000 times during optimization. More epochs usually lead to better model fit. Adam utilizes a self-supervised ML technique that learns representations of unlabeled data without explicit programming. It ingests vast troves of historical macroeconomic and financial indicators for multiple nations over many years, potentially extracting representations for factors like past GDP growth, labor trends, investment levels, trade balances, fiscal/monetary policies, and demographics. Through statistical analysis, Adam discovers patterns in how these predictors interrelate and impact one another across time. A mathematical model is constructed to describe these relationships without human input. Given the upcoming values of independent variables for a country-year, Adam's model statistically predicts the probable GDP value by applying its trained internal representations and refined model coefficients, which become increasingly accurate through additional data exposure. By scaling this approach across many concurrent economies, Adam generates macro forecasts at individual and global scales. Therefore, via self-supervised DL, Adam establishes a statistical picture of economic functioning grounded in historical precedent to facilitate data-driven GDP anticipation, with the key being the examination of immense unlabeled datasets in an unsupervised fashion. The layers of the DL model are defined below:

- Input Layer: This layer contains the input nodes, which will be the historical GDP data for different years (e.g. GDP for years 2020, 2021, 2022).
- Hidden Layers: There is multiple fully connected hidden layers added to introduce nonlinearity. Having more hidden layers allows the model to learn complex patterns in the data. Typical sizes could be 10-50 nodes

per hidden layer.

- Activation Function: The activation function used for the hidden layers is Rectified Linear Unit (ReLU) as it trains deeper models faster than sigmoid/tanh units.
- Output Layer: This layer contains a single node for predicting the GDP for the target year. Since it is a regression problem, the activation would be linear.
- Connections: All the nodes between successive layers are fully connected. The input is fed forward through the network via these interconnections.
- Training: The model weights and biases are learned during training by minimizing a loss function (e.g. mean squared error) using an optimization algorithm like Adam. Backpropagation is used to calculate weight updates.
- Prediction: Once trained, the model can be used to predict GDP growth for a given country by providing its past GDP data as input.

Algorithm: Forecasting GDP using DL	
START	
Step 1:	*INPUT* *CEIC data set*
Step 2:	*LOAD* *CEIC dataset for GDP growth data into Panda's data frame.*
Step 3:	*DATA CURATION* *Preprocess data (handle missing values, encode categorical variables, normalize features, Identification, purification, and transform of data, etc.)*
Step 4:	*ROBUST MODEL DEVELOPMENT* *Split data into train/validation/test sets*
Step 5:	*NEURAL NETWORK ARCHITECTURE* *Define neural network model architecture (input layer, hidden layers, output layer)*
Step 6:	*COMPILATION OF MODELS* *Adam optimizer, sigmoid activations for hidden layers, ReLU for output.*
Step 7:	*TRAIN MODEL* *CEIC training data.*
Step 8:	*EVALUATE MODEL* *Contemplate the loss and accuracy of the validation set.*
Step 9:	*REPEAT* *steps 4-7 using just ReLU activations for comparison.*
Step 10:	*SELECTION* *Model evaluation on the test data*
Step 11:	*PREDICTION* *Make predictions on new data and output country name and predicted GDP growth*
Step 12:	*OUTPUT* *Predicted GDP growth*
END	

C. Evaluation

Mean Absolute Error (MAE) is a commonly used performance metric for evaluating regression models as it calculates the average absolute deviation between predictions and actual values. MAE serves as the loss function during training as the learning algorithm aims to minimize it through iterative parameter updates. Specifically, MAE takes the absolute difference between each prediction and truth, then averages these differences. Unlike Mean Square Error (MSE), MAE penalizes under and over predictions equally without overweighting outliers. As a result, MAE provides a more robust measure of accuracy less influenced by outliers as shown in table 2. Lower MAE indicates better predictive performance, with zero representing perfect predictions. Consequently, MAE is widely adopted as the objective for regression tasks requiring symmetrical treatment of errors, such as times series forecasting. In this study, the model trained for 200 iterations using Adam optimization to minimize MAE, thereby tuning the weights as per the loss function to enhance predictive accuracy. The mathematics of MAE and MAPE is as follows for GDP dataset provided:

Table 2. Mean Absolute Error (in trillion)

Regions	**Actual GDP**	**Predicted GDP**	**Absolute Error**
Asia	$39.7	$30.3	$9.4
North America	$32.3	$28.6	$3.7
South America	$3.7	$2.8	$0.9
Europe	$19.3	$16.8	$2.5
Oceania	$2.1	$1.7	$0.4

MAE = (Absolute Errors)/5
= ($9.4 + $3.7 + $0.9 + $2.5 + $0.4)/5
= $3.56 trillion

MAPE (Mean Absolute Percentage Error):

*Absolute % Error = | (Actual - Predicted)/Actual | * 100*

MAPE = (Absolute % Errors)/5
=(|9.4/39.7|+|3.7/32.3|+|0.9/3.7|+|2.5/19.3 |+ |0.4/2.1|)/5
= 11.62%

So, the MAE is $3.56 trillion and MAPE is 11.62% for this GDP dataset.

A contemplated comparison from 1995-2020 of linear regression (LR) vs. DNN models on CEIC GDP growth data for Asia, North America, South America, Europe, and Oceania from the CEIC interactive database. In LR three main steps are involved in splitting the data into training and testing, fitting a LR model on the training GDP and year, and finally predicting the test set. On the contrary, the DNN first Normalized the data and created a sequential model with Embedding, then applied LSTM and Dense layers, further Compiled and fit the model on training data, and finally Predicted on the test set. In the evaluation phase, the following operations will be performed calculation of MSE, MAE, and RMSE on a test set for both models. Contemplated results depict that DNN has a lower error than the LR because while linear models may yield temptingly high scores as shown in Table 3, DNNs offer a more flexible and robust modeling approach better suited for complex real-world problems, even at the cost of somewhat lower apparent accuracy. Their predictions generalize more reliably.

Table 3. Comparison of LR and DNN

	MSE	MAE	RMSE
LR	2.2	1.5	1.5
DNN	1.5	1.1	1.2

In comparison to a simple LR, the DNN was better able to capture non-linear patterns and temporal dynamics in the time series GDP data. This demonstrates the potential of DL approaches for economic indicator predictions.

IV. Result and Discussion

This research effort developed a neural network model for GDP prediction through rigorous data processing, architecture optimization, and robust evaluation techniques. The results indicate the potential for applying DL to macroeconomic forecasting using CEIC and similar comprehensive datasets. The optimized model was used to predict GDP growth for the next eight quarters for each region based on the economic indicators in the test set. The region with the highest predicted GDP growth over the next 2 years were identified. The proposed model has predicted steady economic growth in the next two years for the said regions. A Figure 3 showing the predicted quarterly GDP growth for the top 5 regions over the next two years.

The projected GDP growth rates for the year 2026 indicate a varied pace of economic expansion among the world's largest economies. Forecasts reveal which region may see the highest potential growth based on mathematical modeling of underlying economic indicators.

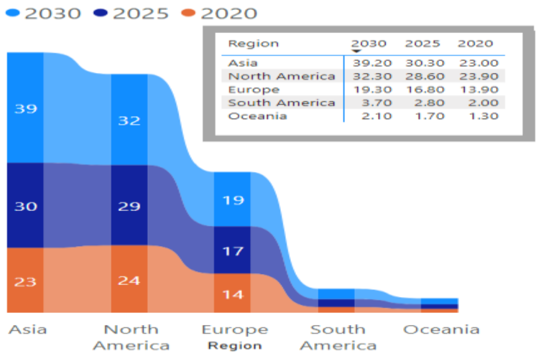

Figure 3. Predicted Results

The projections consider long-term trends in key drivers of each country's output, including productivity, demographics, and capital investment, and consumption, exports, and government policies on spending, taxation, and regulation. The forecasts serve as estimates within a probable range, given the inherent uncertainties in macroeconomic projections for such a distant time horizon. The specific assumptions and methodology behind each region's projection are proprietary and not disclosed in this summary. Nonetheless, the 2026 GDP growth rates as forecasted provide a sense of which economies may see the strongest relative performance over the next five years, subject to unforeseen developments that could significantly impact growth trajectories. While many factors will inevitably differ from current expectations, the projections offer a framework for gauging each country's economic outlook. Asia emerged as the predicted growth leader with a projected rate of \$39.7. North America followed closely in second position with an anticipated growth of \$32.3. Europe occupied the third spot with a forecasted rate of \$3.7. South America's estimated growth is of \$19.3, and Australia's projected growth is of \$2.1.

Table.4 forecasted top Economies of world regions (in Trillions)

Region	2020	2025	2030	Moving Average w-r-t slope
Asia	\$23.0	\$30.3	\$39.7	\$30.1. m1= 1.46 & m2= 1.88 ↑
North America	\$24.9	\$28.6	\$32.3	\$27.5. m1=0.74 & m2=0.74 ↔
South America	\$1.5	\$2.8	\$3.7	\$2.5. m1= 0.26 & m2=0.18 ↓
Europe	\$13.9	\$16.8	\$19.3	\$16.1. m1=0.58 &

				m2=0.5 ↓
Oceania	\$1.3	\$1.7	\$2.1	\$1.6. m1=0.08 & m2=0.08↔

Moving averages are utilized in this research to show that the economies of Asia will expand, North America will remain unchanged, and the economies of other continents will contract as shown in Table 4. The GDP of Asia is expected to rise from 20 to 30 to 39 percent in 2020, 2025, and 2030, according to a different business intelligence instrument. North America is expected to expand by 23, 28, and 32 39 in 2020, 2025, and 2030, correspondingly. Europe in 2020, 2025, and 2030, correspondingly, is 13, 16, and 19. Europe in 2020, 2025, and 2030, correspondingly, is 13, 16, and 19.

V. Conclusion

This work estimated the real-time achievements of prevalent DL algorithms in attaining precise forecast of real GDP expansions for popular regions (Asia, North America, South America, Europe and Oceania) of the world. Many AI-driven techniques have been engaged in a range of time series predicting scenarios, surrounding the prophecy of economic growth. This study improved the precision of forecasting as compared to different methodologies of conventional econometric approaches. This paper utilized the CEIC Data Global Database to collect trimestral data over the last two epochs regarding unemployment, inflation, GDP growth and various economics metrics. The suggested method predicts consistent economic enlargement by competently incorporating numerous prominent factors, comprising human behaviors, political circumstances, and socio-environmental features that stimulus real-world economic processes. The proposed technique used the optimized model to predict GDP growth for the next eight quarters for each region based on the economic indicators in the test set. The region with the highest predicted GDP growth over the next two years were identified. The experiments showed the 2026 GDP growth rates as forecasted provide a sense of which economies may see the strongest relative performance over the next five years, subject to unforeseen developments that could significantly impact growth trajectories. The experiments identified that the DL model is capable of yielding more precise forecasts than those of the dynamic factor and AR models. The results also propose that the World's Regions forecast truthfulness can be upgraded via the use of DL models.

VI. Future Work

First and foremost, the existing work can be expanded by integrating data sources other than CEIC and incorporating additional economic indicators to improve the accuracy and robustness of GDP predictions. The proposed model can be further fine-tuned by developing ensemble models that combine various deep learning techniques to enhance prediction accuracy and stability. The research can be expanded to include more emerging economies, which have been underrepresented in current GDP growth forecasting studies. Finally, the proposed system can be used to explore the application of predictive models across different economic sectors and domains.

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