ISSN: 0975-3583,0976-2833 VOL15, ISSUE 02, 2024

DEEP REINFORCEMENT LEARNING BASED MULTIPREDICTOR ENSEMBLE DECISION FRAMEWORK FOR REGIONAL GDP PREDICTION

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ABSTRACT - Gross Domestic Product (GDP) is a good way to show how the economy is growing and how resources are being used in different areas. It's not enough to just look at a single factor when trying to figure out a region's GDP; you also need to look at factors like schooling, business, jobs, population, and more. It is important for both economics and government to be able to predict regional GDP because it tells us a lot about the economic health and growth of areas. We suggest using a Deep Reinforcement Learning-based multi-predictor ensemble decision system in this project to make area GDP forecasts more accurate and reliable. To train the GDP Prediction, we can use the Gated Recurrent Unit (GRU), the Temporal Convolutional Network (TCN), the Voting Classifier, the XGBooster, and the Deep Belief Network (DBN). These models can predict the data. In a multipredictior ensemble decision structure, a vote algorithm comes to a decision by putting together results from different predictors. The Deep Q-Network (DQN) method quickly checks how well these neural networks change to different GDP datasets so that an ensemble model can be made that gives correct results.

Keywords:- *Deep Reinforcement Learning, GRU, TCN, Voting Classifier, GDP Prediction.*

I. INTRODUCTION

Gross Domestic Product (GDP), which is usually calculated every three months or once a year, is an important economic number that shows how much all the goods and services made in a country were worth in money during a certain time frame. The GDP is a very important measure of a country's economic health and success. GDP is an important tool for economists, investors, decision-makers, and researchers because it helps them make smart choices about economic policies, investments, and business strategies. It also makes it easier to compare how economies are doing in different countries and gives researchers a way to study and predict the economy. It is important to remember that the GDP is not perfect and is not fully responsible for things like equal income, protecting the environment, and maintaining a high standard of living. Because of this, other measures are often added to it to get a better picture of the economic and social health of a country as a whole.

You can figure out the size and growth rate of an economy by getting an idea of its GDP. GDP can be found by adding up investment, production, and income. The GDP can then be changed to account for population and costs to get more accurate results. The foreign balance of trade, investments, growth in private stocks, paid-in building costs, and the total

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amount spent by both individuals and the government all count toward a country's GDP. Exports increase value whereas imports decrease it. The trade balance between nations is crucial. The GDP of a country tends to rise when its people sell more goods and services to other countries than its own people buy from other countries. GDP, which is found by dividing GDP by a country's population, is often used to measure how well off and how well off the people who live there are.

The main goal of the study is to predict the GDP of different areas. Regional GDP projections can help with many things, such as economic planning, allocating resources, and making policy. Predictions of the regional GDP that are right can help people make decisions at both the regional and national levels.The project's goal is to create a system with a lot of predictions. It tries to combine the prediction power of several data sources or models instead of relying on a single model or forecast to figure out regional GDP.By mixing the strengths of different models, this ensemble method is often used to make predictions more accurate.

Effective regional GDP forecasting in economic operation and development may anticipate macroeconomic trends and contribute to healthy macroeconomic growth, as well as ecologically sustainable urban development. The government may forecast and anticipate market economy development to make growth plans and local economy-friendly actions [1]. Technology that can predict GDP can help change the future of sustainable growth in an area.It is the main sign of national economic accounts and a key way to measure the state and amount of growth of an economy.

It will be the key to the next level of social progress if it is used to change the way social resources are planned and distributed while keeping the economy's growth safe and sustainable. Estimating the area GDP can help local governments make better economic and science choices. A lot of experts agree that the standard GDP only looks at the growth of the economy's overall amount and doesn't take into account how natural resources and society affect the economy [2].By mixing the strengths of different models, this ensemble method is often used to make predictions more accurate. The ensemble decision framework may greatly enhance the model's ability to make predictions by mixing different parts in a smart way. Nonlinear modeling, data analysis, and feature extraction may produce this.

II. LITERATURE SURVEY

The literature looked at includes a range of different ways to model and predict the economy, with a focus on China's regional GDP and the bigger picture of economic and environmental change. Li et al. (2022) suggest a three-step feature selection and deep learning method for predicting regional GDP. They show that it works well at catching complex trends in China's economic setting [1]. Li et al. (2022) published another paper that uses deep reinforcement learning to create a multipredictor ensemble decision framework. This makes it even better at predicting regional GDP [2].

Ming et al. (2019) [3] show that fractional calculus can be used in models of Chinese economic growth. Zhou et al. (2021) look into the threshold effect of economic growth on energy usage in wealthy countries. This shows how complexly economic and energy factors interact [4]. In his 2021 paper, Pirgmaier looks at the importance of value theory for

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ecological economics, focusing on how important it is for understanding how economic actions affect the environment [5]. D'amato and Korhonen (2021) suggest a long-term plan for sustainability that includes the bioeconomy, the cycle economy, and the green economy [6].

The research by Wu et al. (2019) looks at how economic downturns affect the use of materials in 157 different countries. Their findings show how economic downturns affect the use of resources [7]. Borio et al. (2020) say that the financial cycle is a key tool for predicting recessions [8]. Cohen et al. (2019) and Myszczyszyn et al. (2021) look into how emissions are no longer linked to GDP in China and how economic growth, energy use, and carbon dioxide emissions are connected in V4 countries [9, 10]. As a whole, this literature gives us a full picture of the different approaches and points of view that help us understand how economies work, how they can last, and how they affect the environment.

III. METHODOLOGY

Modules:

- Data exploration: we will import data into the system using this module.
- Processing: we will read data for processing.
- Data splitting into train and test: we will divide data into train and test using this module.
- Building the model: XGBooster - Voting Classifier (SVC + RF + DT) - MLP - ELM - Based on Elastic Net - RBF - SVM - TCN - GRU - RNN - ESN - ENN - LSTM - CNN + LSTM - DBN - (DQN-TCN-GRU)
- User signup & login: Using this module will obtain registration and login
- User input: Using this module will provide input
- prediction : Final predicted output will be shown on screen

A) System Architecture

System Architecture summarizes the project. Database, features, fundamental models, Q-Learning ensemble technique, and assessment modules comprise the system architecture. These modules forecast GDP.

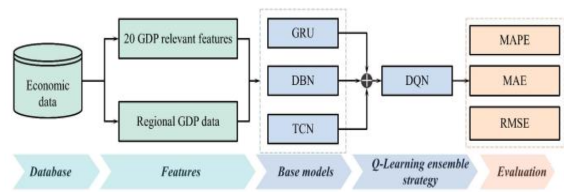

Fig 1: System Architecture

EXISTING SYSTEM

By changing the standard economic growth model for GDP from the point of view of protecting the environment and quality of life, green GDP could be used as a measure. You can also change the GDP path from one that is based on economic growth alone to one that is based on measures of progress like education, health, and life. This means that as the economy grows, everyone in society may gain from the growth of society. So, the GDP needs to be improved even more as a measure of economic progress. It also helps the economy grow, the organization of the economy, and people's living standards. It is necessary for long-term growth.

PROPOSED WORK

For making an exact GDP forecast model, the project uses a complex multi-predictor ensemble decision structure that is based on deep reinforcement learning. The modeling process starts with adding

GRU, TCN, Voting Classifier, XG Booster, Convolution Neural Network (CNN), and DBN as main predictors. These add-ons help train three separate GDP predicting models. After that, the DQN method checks these neural networks' ability to change to different GDP datasets in a planned way, which leads to the creation of an ensemble model. In the last step, the DQN method is used to actively improve the ensemble weight factors of the three neural networks. This gives accurate and flexible GDP prediction results. This new method uses the best parts of deep reinforcement learning and ensemble methods to make GDP forecasts more accurate.

A) Dataset Collection

Regional GDP Prediction Dataset Description

Economic Indicators: Gross Domestic Product (GDP): The main measure that shows how much money different areas make.

Employment Rate: Employment rate is the share of people of working age who are employed. Industrial output refers to the amount of work that is done in important businesses that help the area economy.

Demographic Factors: Population growth is the percentage change in each region's population every year.

Education Levels : Information about the level of education of the population, like what number of people have a college degree.

Industry-specific Data: Sector-wise GDP Contributions : A breakdown of the GDP by industries like services, manufacturing, and agriculture.

Investment in Research and Development (R&D): Money that is spent on activities that lead to new ideas and improvements.

Time Series Data: Time series data that show how each region's GDP has changed over a number of years.

Seasonal and Cyclical Trends: Regular and cyclical trends are the things that cause changes in the economy from time to time.

External Factors: Indicators of the world economy that affect regional GDP, such as global GDP growth, trade flows, and product prices, are examples of external factors.

Policy Changes: Policies made by the government that affect the growth of the area economy.

Environmental Factors: environmental factors Metrics: Signs that show how committed the area is to protecting the earth and using sustainable methods.

Dataset Format: It is organized in a tabular style, with rows for areas and columns for economic, social, and industry-related statistics.

There are both input traits and GDP numbers for the goal time period in each row.

It is possible to see a lot of different trends and differences across areas because the information is big enough.

B) Pre-processing

Several important steps are taken in the preparation part of the suggested Deep Reinforcement Learning (DRL) based multi-predictor ensemble decision system for predicting regional GDP. To begin, data normalization is used to make sure that scales are the

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same across different features. This is necessary because school, business, job, and population data are all very different. Feature engineering is used to get useful data and make input factors that make sense for predicting models. Imputation methods are used to fill in any gaps in the GDP datasets with missing data, which helps train models more thoroughly. Encoding categorical factors makes it easier to use them in machine learning models. In addition, methods for finding and getting rid of outliers are used to make the models more stable. For models like GRU and TCN, time series trends and other temporal features of the data are taken into account. The datasets that have already been cleaned up are then put into the ensemble decision framework, which is made up of GRU, TCN, Voting Classifier, XGBooster, and DBN. This allows for a full regional GDP estimate based on deep reinforcement learning.

C) Training & Testing

Each model in our Deep Reinforcement Learning (DRL) multi-predictor ensemble decision framework for predicting regional GDP is trained on historical regional economic data during the training phase. These models are the GRU, TCN, Voting Classifier, XGBooster, and Deep Belief Network. Gradient descent is used to find the best model parameters so that the gap between expected and real GDP numbers is as small as possible during training. The Deep Q-Network (DQN) method is used by the ensemble framework to test how well these models can fit different GDP datasets. DQN adjusts the weights given to each prediction in the ensemble to get the best accuracy and stability overall.

During this step, the learned ensemble model is tested on data it has never seen before to see how well it can predict the future. Now that the models are part of the ensemble, they each make their own predictions about the area GDP. Using the best parts of each model, the vote algorithm puts these results together to make a final result. The DQN algorithm improves the ensemble's decision-making depending on test outcomes. This makes sure that it can be used in a range of regional economic situations. The project's success is determined by how accurate and precise the end GDP predictions are. These predictions show how well the multi-predictor ensemble decision framework works at improving regional GDP forecasts through deep reinforcement learning.

D) Algorithms.

XGBoost – Extreme Gradient Boosting:

XGBoost is a well-known and useful open-source version of the gradient boosted trees method. An open source machine learning tool called XGBoost is famous for being able to solve supervised learning problems like classification and regression issues. Using gradient boosting methods, it builds a group of decision trees. Then, it puts these decision trees together to make a good prediction model. Combining the predictions of a group of simpler, weaker models is what gradient boosting does to get a good guess at a goal variable.

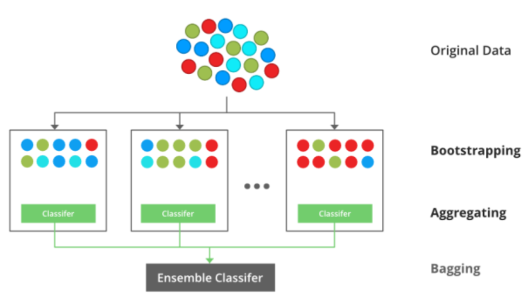

Fig 2 : XGBooster

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Voting Classifier (SVC + RF + DT)

A Voting Classifier is a type of machine learning ensemble model that takes the results from several base classifiers and puts them all together to make a single estimate. Classification and regression are both things that it can be used for. We want to make a Voting Classifier that takes the results from three different classifiers and puts them all together. These are the Support Vector Classifier (SVC), the Random Forest (RF), and the Decision Tree (DT). This group method usually leads to more accurate predictions than putting each algorithm to work on its own. The Voting Classifier can often lower the risk of overfitting and boost generalization, which leads to better results all around. Voting classifiers are machine learning predictors that train several base models or estimators and generate predictions depending on their results. The factors for aggregation can be used to make a decision about each estimate result.

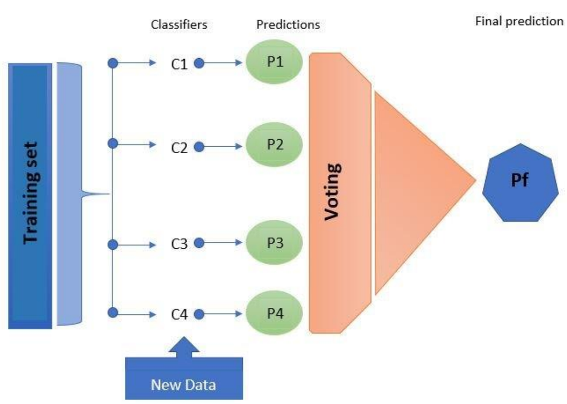

Fig 3 : Voting Classifier

Pseudo code for Voting Classifier:

```
eclf1=
VotingClassifier(estimators=[('lr',clf1),('rf',clf2),
voting='soft', weights=[1,1,2,2,1,3,2])
eclf1.fit(X_train_scaled,y_train)
eclf_predictions = eclf1.predict(X_test_scaled)
acc = accuracy_score(y_test, eclf_predictions)
prec = precision_score(y_test, eclf_predictions)

rec = recall_score(y_test, eclf_predictions)
f1 = f1_score(y_test, eclf_predictions)
from sklearn.metrics import roc_auc_score
roc = roc_auc_score(y_test, eclf_predictions)
model_results = pd.DataFrame([['Voting Classifier',
acc,prec,rec,f1,roc]],
columns =
['Model','Accuracy','Precision','Recall','F1
Score','ROC'])
results = results.append(model_results, ignore_index
=True)
```

MLP:

MLPs, like ABNs, are Artificial Neural Networks used for regression and classification. This neural network is termed a feedforward neural network because data only travels from input to output. There are no loops or return links.MLPs can be used for many things, like figuring out what a picture is, understanding natural language, predicting time series, and more.

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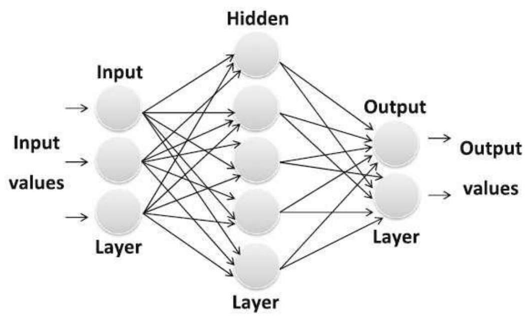

Fig 4 : MLP

SVM:

Support Vector Machine (SVM) is a type of guided machine learning that can do both regression and classification. Even though we talk about regression problems, they work best for sorting. Most of the time, it works best for binary classification tasks, but it can also be used for regression and multi-class classification. SVMs are famous for being able to find the best hyperplane in a high-dimensional feature space to separate data points into different groups.

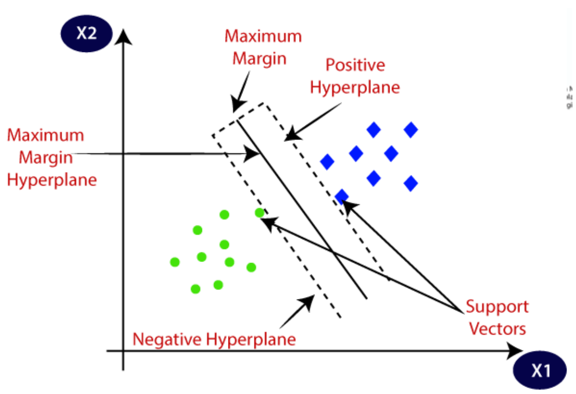

Fig 5: SVM

GRU:

The Gated Recurrent Unit (GRU) is a type of Recurrent Neural Network (RNN) design that was created to fix some problems with traditional RNNs, such as the loss of gradients and long-term dependence. People often use GRUs, which are a type of Long Short-Term Memory (LSTM) network, for sequential data tasks like natural language processing, speech recognition, and time series forecasts. GRUs use less computing power than LSTM networks and can find long-range relationships in linear data.

LSTM:

In the area of deep learning, Long Short-Term Memory networks, or LSTMs, are used. This is a type of Recurrent Neural Networks (RNNs) that might be able to learn long-term connections, especially when predicting sequences.

IV. EXPERIMENTAL RESULTS

A) Comparison Graphs → Accuracy, Precision, Recall, f1 score

Accuracy: A test's accuracy is its capacity to identify weak and strong instances. To measure a test's accuracy, we should record the small fraction of real positive and negative results in fully reviewed instances. This might be expressed numerically:

Accuracy = TP + TN TP + TN + FP + FN.

Precision: Precision quantifies the percentage of positives that are appropriately classified. We may determine accuracy using the formula:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

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Recall: Recall is a machine learning variable that measures how well a model can recognize all relevant examples of a certain class. A model's ability to capture a certain class is measured by the percentage of accurately expected positive perceptions to true benefits.

$$Recall = \frac{TP}{TP + FN}$$

F1-Score: Machine learning assessment measures model accuracy using the F1 score. Consolidates model precision and review ratings. The accuracy measurement calculates how frequently a model predicted successfully throughout the dataset.

$$\text{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\text{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

B) Frontend

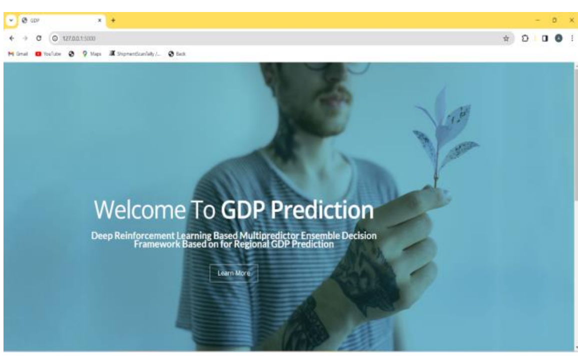

Fig6: Welcome Page

The Welcome page to Predicting GDP can be seen in the picture above.

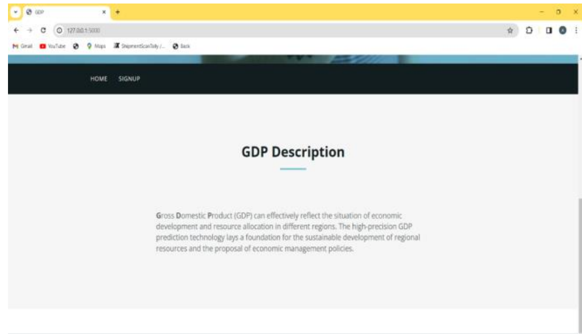

Fig 7: GDP Description

The definition of Gross Domestic Product (GDP) can be seen in the picture above.

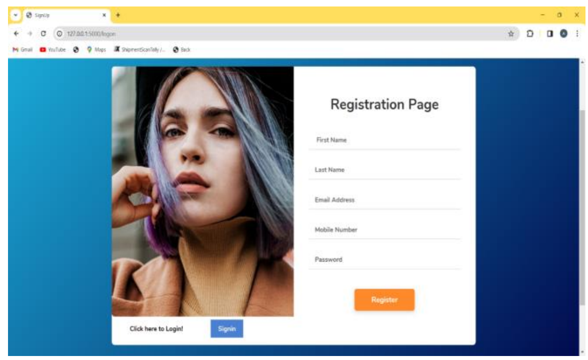

Fig8: Registration page

In the picture above, you can see the Predicting GDP login page.

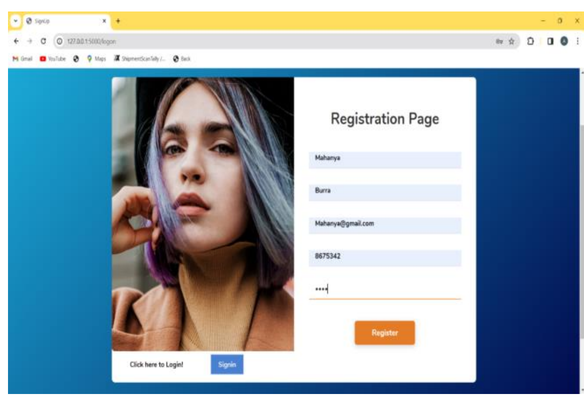

Fig 9: Entering User Details

On the image above, you can see how to put your first and last name, email address, mobile phone

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number, and password on the login page. This page is where users sign up to use Predicting GDP.

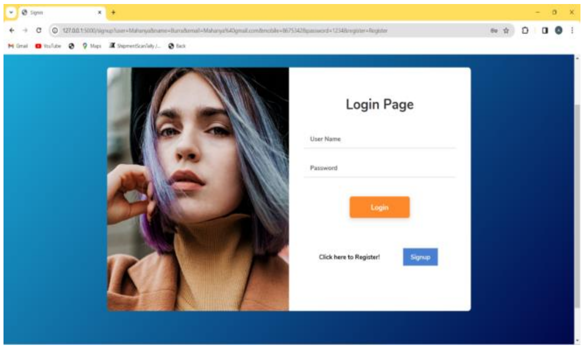

Fig10: Login Page

Sign-in page will be shown on the screen above. Once a person has successfully registered, they can go to the login page.

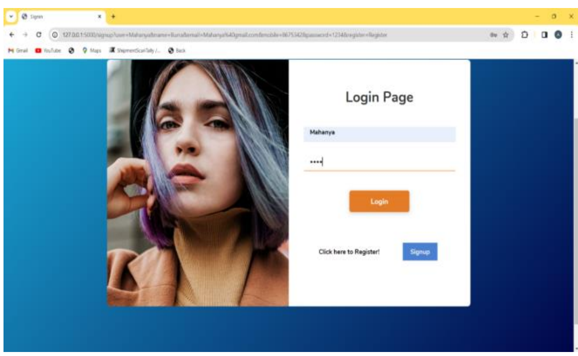

Fig 11: Entering Login Details

Here's a picture of the login page for Predicting GDP. Users can add their information, such as their user name and password.

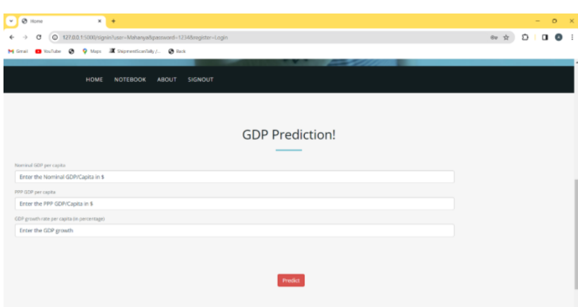

Fig 12: GDP Prediction Page

The picture above will show Predicting GDP once the user has properly registered.

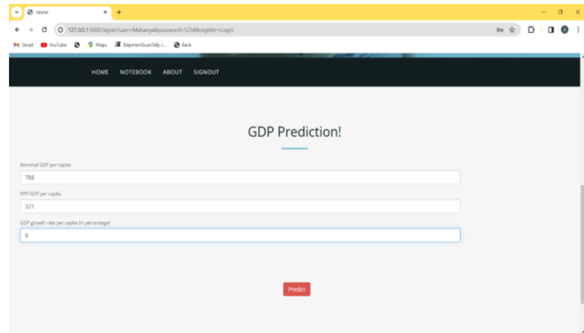

Fig13: Entering GDP Values

The picture above shows how to enter numbers to predict GDP, such as nominal GDP per capita, purchasing power parity (PPP) GDP per capita, and GDP growth rate.

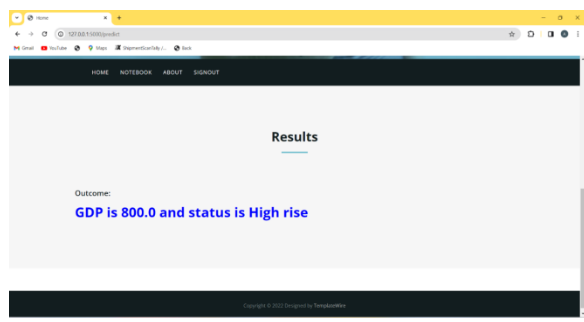

Fig 14: Displays Final Output for GDP

The last thing that Predicting GDP will show is the GDP number and the growth rate (High, Down, Middle, or No Change).

V. CONCLUSION

Gross Domestic Product (GDP) is a key measure of the health of a country's or region's economy and the long-term growth of society. Technology that predicts GDP helps the regional government study and make decisions about economic policy. Deep reinforcement learning is used in this project to come

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up with a Multi predictor Ensemble Decision Framework for predicting GDP. To train the GDP forecast, there are three models: GRU (Gated Recurrent Units), TCN (Temporal Convolutional Network), Voting Classifier, XG Booster, and DBN (Deep Belief Networks). These models can predict the data. In a multipredictor ensemble decision system, a voting algorithm makes a choice by putting together results from a number of different predictors. Unlike regular RNN and shallow neural network frameworks, these three neural networks are better at analyzing the original features of GDP and making accurate predictions thanks to the way they are built. The DQN (Deep Q-Network) method quickly checks how well these three neural networks change to different GDP datasets so that an ensemble model can be made that gives correct results. The DQN algorithm gave us the final data for predicting GDP. There are several GDP datasets that can be used by the DBN, TCN, Voting Classifier, XG Booster, and GRU to make accurate predictions. Features of the industrial organization, past GDP data, and schooling all have a big effect on how well GDP predictions work. In the end, the project does better when the ensemble multi-predictor regional GDP forecast system based on deep reinforcement learning is used.

VI. FUTURE SCOPE

In the coming years, it will be very important to make regional economic growth plans that use GDP predictions and policies that are specific to each area. These tactics will be very important for good governance because they will help governments control the economy on a large scale based on correct GDP predictions. This method that looks to the future makes it easier to make strategic decisions, which gives officials the power to make the best use of resources, promote long-term growth, and deal with new problems that come up in regional economies. By making sure that policies are in line with what they think will happen in the future, governments can make the economy more stable and help areas grow. This keeps growth goals in line with how the economy is changing.

REFERENCES

[1]LiQingwen, YanGuangxi, and YuChengming,“A Novel Multi-Factor Three-Step Feature Selection andDeep Learning Framework for Regional GDP Prediction:Evidence from China”Sustainability vol. 14, p. 4408, 2022.

[2] Li Qingwen, Yu Chengming, and Yan Guangxi, “ A New Multipredictor Ensemble Decision

Framework Based on Deep Reinforcement Learning for Regional GDP Prediction”, vol. 10,45267, May. 2022.

[3] H. Ming, J. Wang, and M. Fečkan, ‘‘The Application of Fractional Calculus in Chinese Economic Growth Models,’’ Mathematics, vol. 7, no. 8, p. 665, Jul. 2019.

[4] J. Zhou, Z. Ma, T. Wei, and C. Li, ‘‘Threshold effect of economic growth on energy intensity—Evidence from 21 developed countries,’’ Energies, vol. 14, no. 14, p. 4199, 2021.

[5] E. Pirgmaier, ‘‘the value of value theory for ecological economics,’’ Ecol. Econ., vol. 179, Jan. 2021, Art. no. 106790.

[6] D. D’amato and J. Korhonen, ‘‘Integrating the green economy, circular economy and bioeconomy in a strategic sustainability framework,’’ Ecol. Econ., vol. 188, Oct. 2021, Art. no. 107143.

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[7] Z. Wu, A. Schaffartzik, Q. Shao, D. Wang, and G. Li, ‘‘Does economic recession reduce material use? Empirical evidence based on 157 economies worldwide,’’ J. Cleaner Prod., vol. 214, pp. 823–836, Mar. 2019.

[8] C. Borio, M. Drehmann, and F. D. Xia, ‘‘Forecasting recessions: The importance of the financial cycle,’’ J. Macroecon., vol. 66, Dec. 2020, Art. no. 103258.

[9] G. Cohen, J. T. Jalles, P. Loungani, R. Marto, and G. Wang, ‘‘Decoupling of emissions and GDP: Evidence from aggregate and provincial Chinese data,’’ Energy Econ., vol. 77, pp. 105–118, Jan. 2019.

[10] J. Myszczyszyn and B. Suproń, ‘‘Relationship among economic growth (GDP), energy consumption and carbon dioxide emission: Evidence from V4 countries,’’ Energies, vol. 14, no. 22, p. 7734, 2021.