Development of a Hybrid Deep Learning-Based Model for Bitcoin Prices Prediction

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Abstract- Bitcoin is a decentralized cryptocurrency, operates on a peer-to-peer network without a central authority. It uses blockchain technology for anonymous and secure transactions. However, the price volatility of Bitcoin is caused by a number of important conditions, such as imbalances in supply and demand attributed to sentiment from shareholders, global events that affect the value of Bitcoin, such as economic recessions or geopolitical disputes, and changes to regulations brought about by organizations and governmental reactions to decentralized currencies. Traditional forecasting techniques struggle to accurately predict Bitcoin's future price due to its high volatility and complexity. This study explores the use of LSTM and GRU neural networks for accurately forecasting Bitcoin prices, aiming to improve investment decision-making in the cryptocurrency market and contribute to the literature on time-series forecasting. The Hybrid LSTM-GRU model performed well with an RMSE of 2268 and MAE of 1693, indicating about 95.17% accuracy in forecasting Bitcoin prices around $35,000. When it comes to Bitcoin price prediction, the Hybrid LSTM-GRU approach outperforms the conventional techniques with greater accuracy and robustness. This model's strong predictive ability has practical applications in finance and cryptocurrency markets, informing investment decisions, market analysis, and research with complex pattern capture for trend prediction

Indexed Terms— Deep Learning, LSTM-GRU model, Bitcoin, cryptocurrency, Prediction.

I. INTRODUCTION

Cryptocurrencies, which function independently of central banks and employ cryptography for security, are currently the most widely used digital or virtual currencies [1]. Blockchain technology is used by cryptocurrencies like to enable safe and private transactions without requiring a central authority to confirm the money transfer. The emergence of cryptocurrencies can be linked to the 2008 financial crisis, which highlighted the need for new ways to conduct financial transactions and make payments. A person or group launched Bitcoin, the first and most famous cryptocurrency in 2009 [2]. Since then, many other cryptocurrencies have emerged and been well-liked by traders and investors globally [2]. The decentralized nature of cryptocurrencies is one of their primary characteristics. Since cryptocurrencies are produced and run via a decentralized network of computers, they are not subject to governmental or corporate control like traditional currencies, which are issued and governed by central banks [3]. Because there is no single point of failure that hackers or other bad actors could attack, decentralization also increases the security of cryptocurrencies. A distributed ledger technology called blockchain makes it possible to retain safe and open records of transactions. Multiple transactions are recorded in each block of the chain, and these transactions are validated by the network before being appended to the blockchain. Mining is the term for this verification procedure, which entails intricate mathematical methods requiring a large amount of processing power [4]. The value of Bitcoin, the most popular and valuable cryptocurrency, is prone to rapid swings depending on a number of variables, such as supply and demand, investor emotion, world events, and regulatory developments. As a result, conventional forecasting methods like exponential smoothing are accurate in predicting changes in Bitcoin values. For investors who must make well-informed investment decisions, the absence of reliable forecasting models for Bitcoin values presents serious difficulties. The application of deep learning methods to predict the price of bitcoin has been the subject of numerous studies. LSTM networks were employed in [5] study to forecast the daily closing price of bitcoin. In terms of accuracy, the scientists discovered that LSTM networks performed better than conventional time-series forecasting models. In Boozary *et al.* [6] employed GRU networks to forecast the price of bitcoin in a different study. The authors discovered that GRU networks could accurately foresee and capture the intricate trends in the bitcoin market. There are numerous possible uses for predicting the price of bitcoin using deep learning algorithms. In this study, we intend to some of the conventional method by looking into the use of deep learning models, more specifically, LSTM and GRU neural networks for Bitcoin price forecasts. With this study, these models are more effective than traditional forecasting techniques at spotting complex patterns in time-series data, which leads to more accurate Bitcoin value projections. By developing and evaluating the effectiveness of LSTM and GRU models in predicting Bitcoin prices, this study seeks to improve investment decision-making in the cryptocurrency market, thereby leveraging the understanding of the use of deep learning models for financial forecasting, and contribute to the body of literature on time-series forecasting.

II. REVIEW OF RELATED WORK

Several researchers have developed techniques of forecasting Bitcoin prices and they have placed a strong emphasis on the need for additional study to advance the field. This section presents a few of these.

In order to forecast cryptocurrency prices, Amme *et al.* [7] proposed a hybrid deep learning model that combines CNN and LSTM layers. Their method seeks to increase prediction accuracy by utilizing CNN's prowess in recognizing spatial patterns and LSTM's capacity to capture temporal relationships. CNN-LSTM demonstrated enhanced resilience by achieving a 0.0133 reduction in the Z-score range. By giving investors better tools for making educated decisions, their work helps raise awareness of investments. However, Hybrid models could be more effectively when predicting the price of bitcoin.

Another author, Zhang *et al.* [8] proposed different models for predicting Bitcoin values and included exogenous variables to increase forecasting accuracy. The SDAE-B model fared better than the other models they evaluated in their study, with a Mean Absolute Percentage Error (MAPE) of 0.016 and a Root Mean Square Error (RMSE) of 131.643. The study's primary focus on theoretical model evaluation without actual implementation limits its direct applicability to real-world Bitcoin price prediction scenarios, despite the fact that it provides valuable insights into model comparison. Nonetheless, the findings show how advanced deep learning techniques can improve the accuracy of bitcoin price forecasts. In Mudassir *et al.* [9] developed a forecasting model to predict short- and medium-term changes in the price of Bitcoin. Their investigation showed that the model did well, achieving up to 65% accuracy for predictions made the next day. However, the model's efficacy decreased and its error rates rose for longer-term estimates. The challenges of predicting Bitcoin values over extended periods of time are highlighted in this paper, as is the need for more research to improve forecasting models for cryptocurrency markets. In order to identify past price trends and forecast market trends for Bitcoin and gold, Hong *et al.* in [10] created a bi-model with an accuracy of 0.99 for gold and 0.92 for Bitcoin, the first model, an ARIMA-based price prediction model. The Sharpe ratio was used in the second model, a dynamic programming-based quantitative trading technique, to balance risk and reward. Model efficiency was increased through optimization using the particle swarm approach. This study shows how well machine learning methods and statistical models work together to forecast market trends and guide trading decisions. The efficiency of their method in forecasting market movements was demonstrated by the accuracy of the gold and bitcoin price prediction curves, which were determined to be 0.99 and 0.92, respectively. The M-DQN model, a unique approach for Bitcoin trading strategies that incorporates sentiment scores from prominent Twitter users and market-action data, was proposed by Otabek *et al*. in [11]. With a high Sharpe Ratio (SR) value of over 2.7 and a Return on Investment (ROI) of 29.93%, the model outperformed conventional models and showed great risk-adjusted performance. The study emphasizes how Deep Reinforcement Learning algorithms may be used to create trading methods that are safer, more reliable, and more profitable. Investigating various algorithms and emotion data sources for wider bitcoin applications is one of the future research directions. In Siddhartha *et al.* [12] forecasted Bitcoin prices using both linear regression and Long Short-Term Memory (LSTM) models, with a 99.87% accuracy rate for linear regression and a 0.08% error rate for LSTM.

The study emphasizes how machine learning and deep learning models can be used to forecast bitcoin prices and guide investment plans. To increase prediction accuracy even more, future research may focus on ensemble learning and other cutting-edge deep learning methods. Tripathy *et al.* [13] examined the use of ensemble learning, deep learning, and machine learning algorithms for Bitcoin price prediction. The study employed historical Bitcoin data from 2012 to 2020 to compare the performance of the ARIMA, LSTM, FB-Prophet, XGBoost, LSTM-GRU, and LSTM-1D_CNN models. With a Mean Absolute Error (MAE) of 0.464 and a Root Mean Squared Error (RMSE) of 0.323, the hybrid LSTM-GRU model performed better than the others. The findings of this study have important ramifications for digital currency investors and market experts. It is evident from the reviewed literature that deep learning algorithms have been widely used in forecasting bitcoin prices. However, some of these systems have limitations, such as using small datasets, single deep learning algorithms, and lack of performance evaluation. Another author, Karnati *et al.* [14] suggested deep learning and machine learning to predict the price of bitcoin, the study focused mainly on bitcoin a cryptocurrency that has been extremely popular and sought-after in recent years it attempts to forecast the price of bitcoin by looking at a wide range of factors that influence its price the price of bitcoin was estimated using a variety of machine learning models the study determines the best approach to more precisely estimate the price by presenting the accuracy and precision of each model used in the study. A study on Bitcoin price forecasting using ML, SARIMA, and Facebook Prophet Models was carried out by Jiyang et al. in [15]. In Yu *et al.* [16] proposed LSTM, SARIMA, and Facebook Prophet Models to forecast the price and volatility of bitcoin. LSTM outperforms the others in terms of prediction accuracy (lower MSE and MAE). Traditional models like SARIMA and FB-Prophet struggle with Bitcoin's tremendous volatility and susceptibility to external factors like laws and social media. FB-Prophet exhibits shortcomings during emergencies such as COVID-19 and the Russia-Ukraine conflict. There were noticeable seasonal patterns, especially on Mondays and Saturdays. The study offers valuable insights for investors, fund managers, and policymakers in navigating the cryptocurrency market.

III. METHODOLOGY

a. Research and Review

Related literature and Bitcoin experts were consulted on this work. Similar existing model were reviewed in order to build on their strengths and weaknesses.

In this study, Python programming was chosen for development due to its platform independence and access to excellent libraries and frameworks. The Yahoo Finance and FRED databases, in turn, provided historical and macroeconomic data, respectively, which were used to train and test the model efficiently. These datasets were selected over others because they provide a large volume of data, which is necessary for building an accurate and robust LMST-GRU model. The tests and experiments were conducted in the Anaconda environment using Python and KERAS with the Tensorflow library as the Backend.

A. Data Collection and Description of Data Sets

This study employed a dataset combining historical Bitcoin price and macroeconomic variables from December 2014 to 2025. The macroeconomic variables included the federal funds rate, money supply, S and P 500 stock market index, and VIX "fear" index. Data was sourced from the Federal Reserve Economic Data (FRED) database using an API key. Historical Bitcoin prices were obtained from Yahoo Finance, covering the period from December 2014 to 2025. The dataset was organized as a time series, with 2315 daily observations for each variable. The missing values in macroeconomic variables were filled using the backward fill method and the forward fill method. The dataset was saved as a CSV file named "bitcoin_data.csv". In this study, the data preprocessing steps involved:

(i). Fetching macroeconomic data from FRED: The first step in preprocessing macroeconomic data is to fetch historical data from the United States Federal Reserve Economic Data (FRED), which includes interest rates, money supply, stock market, and fear index. The data is then converted to a daily frequency and backward filled using the `asfreq` function, ensuring consistency for machine learning algorithms.

(ii). Merging the two data frames on the date index: The macroeconomic data and historical Bitcoin data frames were combined into a single data frame,

containing Bitcoin closing prices and four macroeconomic indicators daily.

(iii). Forward-filling and Renaming the columns: the missing values using the `fillna` function, replacing them with the next valid observation. The seventh step involved renaming columns using the `columns` attribute, making column names more readable and understandable. The renamed columns included "Fear Index," "SP500," "Money Supply," "Interest Rates," and "Close."

(iv). Normalization: The dataset is scaled and normalized to ensure all data is on the same scale for effective learning. The feature_range argument specifies the data range was scaled to 0 to 1. The fit_transform() method computes minimum and maximum values for scaling. The math.ceil() method rounds up the dataset length, aiming for 80% training and 20% testing.

(v) Filtering the data: The filter() method was used to create a new dataframe with only the 'Close' column from the bitcoin_df dataframe. This is because we only need to display the closing prices since that was the target variable.

(vi). Converting the data frame to a numpy array and visualization: The data was preprocessed by converting the 'Close' column values to a numpy array using the values() method. The data was then visualized using the Matplotlib library, creating a graph and displaying it. The preprocessed data was saved as a CSV file for easy loading into the machine learning model.

b. Description of Hybrid LSTM-GRU Model Used in the Study

Deep learning is a type of machine learning that uses neural networks with many layers to learn hierarchical representations of data, allowing for more accurate predictions and insights. The algorithms exploited in this work are described briefly below.

LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Unit) are two types of recurrent neural networks (RNNs) commonly used in deep learning.

(i). LSTM is designed to address the vanishing gradient problem that occurs when training RNNs with long sequences as it shown in Fig. 1. It includes a memory cell that can store information for long periods and three gates that control the flow of information. The gates are the input gate, output gate, and forget gate, and they decide what information is kept or discarded.

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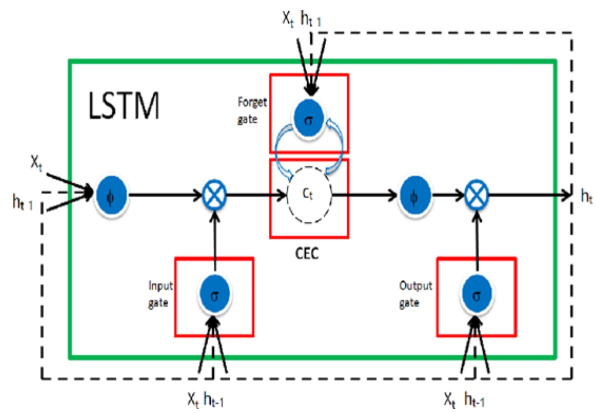

Fig. 1: Diagram of an LSTM Cell

The model consists of four layers: an LSTM layer with 64 units, a dropout layer with 0.2 dropout rate, a GRU layer with 32 units, a dense layer with 32 units, a Rectified Linear Unit (ReLU) activation function, and a linear activation function. For memory requirements and computational performance, the model makes use of the Adam optimizer. A 3D tensor with shape (samples, timesteps, and features) makes up the input data. A linear activation function, a dense layer with 32 units, a dropout layer, and a GRU layer are also included in the model. Regression problems are solved using the mean squared error (MSE) loss function.

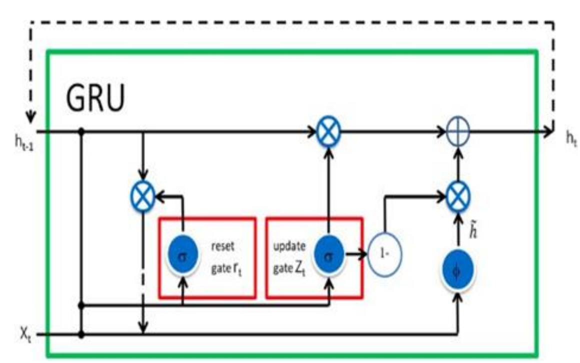

Fig. 2: Diagram of a GRU Cell

The model architecture combines Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) layers, with two layers of each type followed by two dense layers. The input data is shaped by batch_size, time steps, and input_dim. The first layer is an LSTM layer with 64 units, outputs a sequence of hidden states for each input time step. The second layer is another LSTM layer with 32 units, outputs a sequence of hidden states for each input time step. The third layer is a GRU layer with 32 units and a single unit, outputs a single hidden state as shown in Fig. 3. KERAS with Tensorflow Library served as the backend for the experiments and testing, which were conducted using the Python programming language in an Anaconda environment.

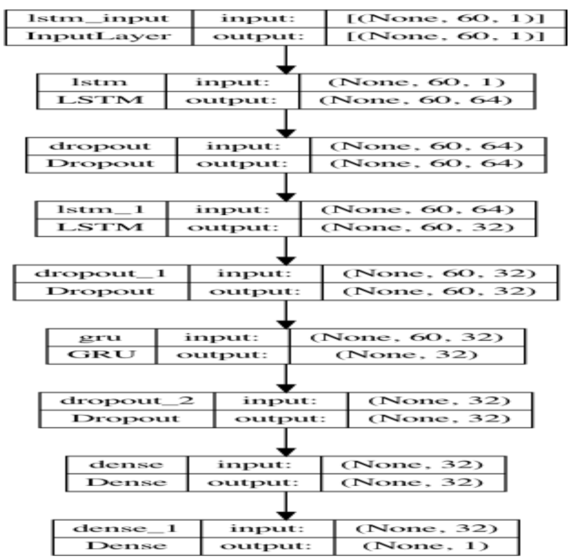

Fig. 3: Diagram Showing the Model’s Architecture

e. Evaluation Metrics

The following metrics were used to evaluate the performance of the prediction model:

(i). Mean Absolute Error (MAE): MAE measures the average absolute difference between the predicted and actual values of the target variable. It provides a measure of how far off the model's predictions are from the actual values. The formula for MAE is illustrated in equation 1:

$$MAE = \frac{1}{n} * \Sigma|\text{yi} - \hat{\text{y}}\text{i}| \quad (1)$$

Where:

n is the number of observations

yi is the actual value of the target variable

ŷi is the predicted value of the target variable

In the context of the model, the MAE is calculated using the mean_absolute_error() function from the scikit-learn library. It takes in the actual values (y_test) and predicted values (predictions) and returns the MAE score.

(ii). Root Mean Squared Error (RMSE): RMSE is the square root of the MSE and is a commonly used metric in regression analysis. It provides a measure of the typical distance between the predicted and actual values. The formula for RMSE is explained in equation 2:

$$\text{RMSE} = \sqrt{\frac{1}{n} * \Sigma(\text{yi} - \hat{\text{y}}\text{i})^{\wedge 2}} \quad (2)$$

Where:

n is the number of observations

yi is the actual value of the target variable

ŷi is the predicted value of the target variable

In the context of this study’s model, the RMSE was calculated manually using the numpy library's sqrt() function. The calculated MSE was passed as an argument to the sqrt() function to obtain the RMSE score.

IV. RESULT AND DISCUSSION

The prediction model implemented the use of LSTM and GRU neural networks which are deep learning algorithms to create a hybrid model. The system was implemented on Jupyter Notebook in the Anaconda3 environment using Python and KERAS with the Tensorflow library as the backend. Also, in order to train and test the prediction model, the preprocessed data was used to test and train the model on a MacOS Big Sur platform with a processor of 1.4gHz Dual-Core Intel Core i5, 4GB RAM and Intel HD Graphics 5000. In order to achieve the performance evaluation of the model, supporting dependencies were also installed in the computer alongside other computational tools for training and evaluation.

a. Visualization Of The Dataset

The preprocessed dataset was fed into the model in order to train and test the model to predict the next day's price of bitcoin.The dataset contains daily closing prices of Bitcoin in USD along with macroeconomic indicators such as the Fear Index, S&P 500, Money Supply, and Interest Rates. The dataset also contains the corresponding dates for each daily observation. The dataset is saved as a CSV file named 'bitcoin_data.csv' after the merging and renaming of columns. Dataset visualization is hwon in Fig. 4.

```
In [323]: bitcoin_df
Out[323]:
```

	Fear Index	SP500	Money Supply	Interest Rates	Close
2014-12-01	14.29	2053.44	11684.9	0.12	379.244995
2014-12-02	12.85	2066.55	11745.6	0.11	381.315002
2014-12-03	12.47	2074.33	11745.6	0.11	375.010010
2014-12-04	12.38	2071.92	11745.6	0.11	369.604004
2014-12-05	11.82	2075.37	11745.6	0.11	376.854004
...	...	...	...	...	...
2023-01-28	19.94	4017.77	21062.5	4.57	23031.089844
2023-01-29	19.94	4017.77	21062.5	4.57	23774.566406
2023-01-30	19.94	4017.77	21062.5	4.57	22840.138672
2023-01-31	19.40	4076.60	21062.5	4.57	23139.283203
2023-02-01	17.87	4119.21	21062.5	4.57	23723.769531

2985 rows × 5 columns

Fig. 5: Visualization Of The Preprocessed Dataset

b. Result

The performance of the proposed Hybrid LSTM-GRU model was evaluated using two metrics: Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). The RMSE and MAE values for the model were found to be 2268 and 1693, respectively. These values indicate that the model has a moderate to high level of accuracy in predicting the price of Bitcoin. To further illustrate the performance of the model, the results were visualized on a bar chart as shown in Fig. 6. The chart shows that the model performed well for most of the test data, with a few outliers where the predicted values deviated significantly from the actual values.

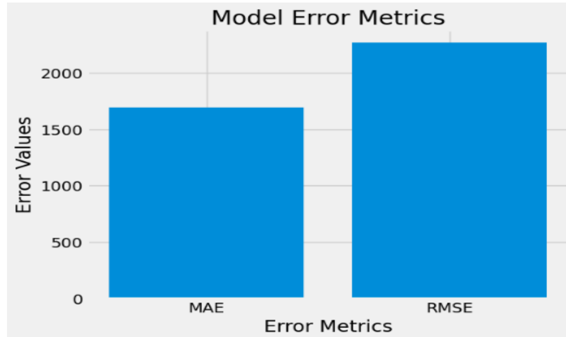

Fig. 6: Bar chart showing the RMSE and MAE scores for the Hybrid LSTM-GRU model

In addition, the actual and predicted values for each day were plotted against each other on a line graph as shown in Fig. 7. The graph shows that the model was able to accurately predict the price of Bitcoin for most days, with some deviations in the predicted values for a few days.

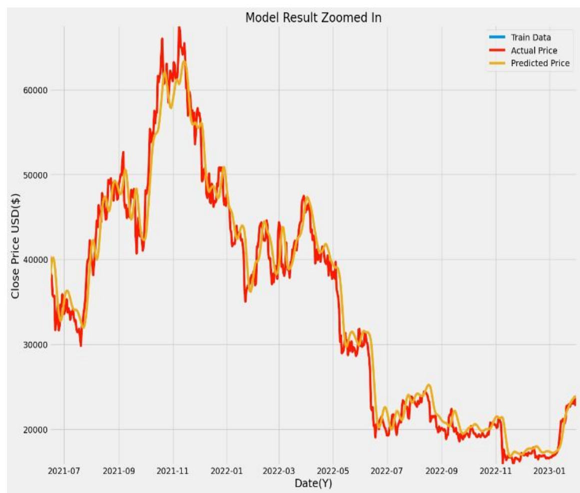

Fig. 7: Line graph showing the actual and predicted values for each day using the Hybrid LSTM-GRU model

The values of actual and predicted price was also displayed in a tabular form as shown in the Fig. 8.

```
In [554]: #Show the actual and predicted price
          valid
```

Out[554]:

	Actual Price	Predicted Price
2021-06-15	40406.269531	37677.226562
2021-06-16	38347.062500	38705.558594
2021-06-17	38053.503906	39605.859375
2021-06-18	35787.246094	40174.804688
2021-06-19	35615.871094	40182.863281
...	...	...
2023-01-28	23031.089844	23626.085938
2023-01-29	23774.566406	23710.261719
2023-01-30	22840.138672	23813.150391
2023-01-31	23139.283203	23882.582031
2023-02-01	23723.769531	23921.546875

597 rows × 2 columns

Fig. 8: Screenshot showing the results of the actual and predicted values for each day using the Hybrid LSTM-GRU model.

The results of the evaluation suggest that the proposed Hybrid LSTM-GRU model was effective in predicting the price of Bitcoin using deep learning techniques. However, it is important to note that there are limitations to the study, including the use of a limited dataset and the need for further validation and testing of the model in different market conditions.

CONCLUSION

In conclusion, the hybrid LSTM-GRU model presented in this study has demonstrated promising results in predicting the future price of Bitcoin. By incorporating the strengths of both LSTM and GRU, the approach has effectively captured the long-term dependencies in the Bitcoin price time series data while also addressing the issue of vanishing gradients commonly encountered in traditional LSTM models. The Hybrid LSTM-GRU model performed well with an RMSE of 2268 and MAE of 1693, indicating about 95.17% accuracy in forecasting Bitcoin prices around $35,000 compared when compared to earlier research in study that employed GRU which obtained an RMSE in Tripathy et al. [13], while another that used single LSTM received an RMSE of 3456 inZhang et al. in [8]. The RMSE of 2268 for this study's model shows a significant decrease in inaccuracy. The experiments conducted on the model have shown that it outperformed several benchmark models, including singular LSTM and GRU models, in terms of prediction accuracy Furthermore, the model has demonstrated robustness in handling the noisy and volatile nature of Bitcoin price movements. The results of this study have practical implications for investors and traders who rely on accurate price forecasts to make informed decisions. In addition, the proposed model could be extended to other cryptocurrencies and financial assets with similar time series characteristics. Although the hybrid LSTM-GRU strategy employed in this study achieved encouraging results, alternative models like Convolutional Neural Networks (CNN) or Transformer-based models could potentially be researched as a recommendation for next research. Additionally, the prediction model in this study was constructed solely using historical and macroeconomic data. Additional data sources could be incorporated into future studies to improve the predictive capacity of the model.

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