Advanced Forecasting with AEGRU: A Robust Approach for Stock Market Time Series

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Abstract: Predicting the stock market's closing price accurately and reliably is complicated. By learning from past market behavior, deep learning algorithms can potentially forecast future price movements with some accuracy. Large volumes of historical stock data can be analyzed by deep learning (DL) to find trends and correlations that support predictive modeling. Deep learning algorithms may be able to predict future price changes with a certain level of accuracy by learning from historical market activity. Autoencoders (AE) retrieve features that recognize important data patterns. The study offers a Gated Recurrent Unit (GRU) model with intricacies in stock market prediction, such as market volatility and complicated patterns for the model's performance. A single dataset's impressive performance does not establish the model's durability. The proposed model is split into 80% training data,10% testing, and 10% validation data The study justifies the model's stability and extensibility by doing a thorough comparison analysis on 30 datasets of companies' stocks, accomplishing an average Mean Squared Error (MSE) of 0.001, Mean Absolute Error (MAE) of 0.021, and Max error of 0. 213. In addition to our novel strategy, we retrained previously employed deep learning models using the same dataset for validation to evaluate our suggested model's contribution. Furthermore, we contribute this offers vital information for improving future stock market prediction models by revealing the distinct contributions of each component to determine the stock closing price.

Keywords: Autoencoder; Gated Recurrent Unit; Neural Network; Stock Price Prediction

1. Introduction

The endeavor to forecast the future value of a company's stock or other financial instrument traded on an exchange is known as stock market prediction[1)]. A substantial profit could be made if the future price of a stock is accurately predicted. The efficient-market theory states that stock prices fairly represent all available information, and any price adjustments that aren't predicated on newly revealed facts are, therefore, inherently surprising. Others have a different opinion, and those who do have a variety of tactics and tools that seem to enable them to forecast future prices.

Stock market trends depend on several factors, and predicting them requires in-depth examination[2)]. Its complexity draws attention because it plays a crucial part in influencing financial decisions, yet its elusiveness highlights how difficult it is to achieve constant accuracy. The inherent volatility, non-linear patterns, and insufficient historical data make it challenging to develop a prediction model utilizing deep learning for stock markets that can effectively capture all market characteristics. Furthermore, modeling is made more difficult by exogenous events and market emotions. Many traditional techniques with roots in statistical modeling have been introduced in the time series prediction analysis field. These tactics include moving average, auto-regression, and linear regression, frequently summarized in the ARMA framework[3-4)]. It is an effective method for managing time series data that develops across several instances. This model combines different data aspects by using a moving average component that tends to one feature and an autoregressive component that addresses another.

Notable mentions include ARCH, LSTM[5-6)], BiLSTM, CNN-BiSLSTM-based hybrid model[7)], and GARCH models[8)]. The subtle variations in time series data are taken into account by these models. As a result, several models

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that show exceptional effectiveness in predicting and analyzing volatility patterns have been put forth[9]. This variety of models is essential for understanding the dynamics of time series data. Our study tackles several issues raised by earlier research on stock market forecasting. To address the issue brought up by[10], which lacked such comparisons, we first do a comparative analysis, evaluating our hybrid architecture based on the AE-GRU model with current approaches. The advantage of our suggested paradigm is demonstrated by this comparison. Second, our research highlights the significance of data quality and noise handling, especially when using 30 real-life companies' stock data for stock market prediction, whereas[11] concentrates on outlier mining algorithms. This addresses a worry[12] regarding the robustness and dependability of our forecasting model. Additionally, our study addresses a limitation[13] by extending the forecast horizon beyond daily fluctuations to capture longer-term trends in stock prices. Our work focuses on predictions for longer-term trends in addition to daily price fluctuations. In contrast to the narrow range of predictions[13], our research expands the value of our approach for traders and investors by attempting to forecast price changes over a larger time frame. In addition, compared to research that concentrates on a small number of companies[14-15], **the** hybrid AE-GRU model is trained and assessed on a larger collection of company stocks, which enhances the generalizability of its conclusions. Our work offers a thorough method for predicting the stock market, resolving several issues raised by earlier research, and advancing a stronger comprehension of predictive modeling in the financial industry.

An architecture based on the AE-GRU model that predicts stock closing prices that are close to reality and achieves a notable level of accuracy when predicting stock prices on test data. An AE-GRU model can capture intricate patterns, achieve superior predictive accuracy, and exhibit robustness and scalability. This model can be applied in real-time situations for stock market prediction. GRU networks excel at determining what will happen next in a sequence, perfect for time-based data like stock market data. Autoencoders are brilliant at identifying intricate, challenging patterns in data. Combining these two yields the greatest results from both models, enabling us to identify every intricate variable needed to effectively forecast future stock prices.

This study's contribution is as follows. The study presents a novel method of stock market prediction by fusing an Autoencoder with GRU networks. This hybrid model leverages the advantages of both architectures to improve prediction accuracy. We propose an AE-GRU-based custom architecture for predicting stock prices accurately on 30 companies' datasets with an average Max Error of 0.213, an MAE of 0.021, and an MSE of 0.001, as shown in Table 4. Research helps make its conclusions more broadly applicable by testing, training, and validating the AE.GRU model on a larger collection of firm stocks. We employ a common dataset, indicated in Table 5, to evaluate our model's performance with popular DL techniques to ensure contribution.

By creating the suggested model on the Nifty 50 dataset (2000–2021), this study expands the forecast timeframe to capture longer-term trends in stock prices, in contrast to other studies that only looked at daily changes. This improves the model's applicability for traders and investors and resolves a weakness noted in earlier research.

The paper is systematically structured into several important sections that focus on methodology and the findings of the research. In Section II, we examine the previous research, and Section III focuses on the methodology. Moreover, the performance of the suggested model is explained in Section IV. Discussions and Limitations are explained in Section V. Conclusion and Future Work are mentioned in Section VI. The abbreviation used in the paper is mentioned in Table 1.

Table 1: Abbreviation of the used term

LSTM	Long-Short Term Memory
ARMA	Auto Regressive Moving Average
ARCH	Auto-Regressive Conditional Heteroskedasticity
BiLSTM	Bidirectional Long-Short-Term Memory
CNN-BiLSTM	Convolutional Neural Network Bidirectional Long-Short-Term Memory
GARCH	Generalized Autoregressive Conditional Heteroskedasticity

2. Literature Review

Predicting stock market trends is a challenging endeavor with substantial ramifications for financial decision-making. The study[10] suggests an LSTM-based prediction model that has an accuracy of 83.88% for stock market forecasting utilizing Nifty Fifty datasets. However, the study does not mention comparisons with other forecasting models or methods. This makes it difficult to ascertain whether the LSTM model is indeed better than current methods. The research[11] proposes a unique outlier mining approach for detecting anomalies in high-frequency tick-by-tick stock market data using volume sequences. Although the author's comparison of the algorithm's performance with conventional cluster analysis (such as k-means) is a positive first step, it does not ensure that the innovative method is better for all stocks or in all situations. An SVM-based model is put forth by the authors[12] to forecast stock prices using the efficient market hypothesis. After retrieving the stock comment data from social media, they preprocess the information to create emotion vectors. Nevertheless, social media data can be noisy and contain inaccurate or irrelevant information.

Before making inferences, it is imperative to guarantee the quality of the data and deal with noise.

Autoencoder long short-term memory (AE-LSTM) networks are proposed in another study[13] as a way to anticipate the closing price of stocks. Nonetheless, forecasting "daily" pricing is mentioned in the report. For traders and investors wishing to make longer-term decisions, the model's utility may be restricted if it can only generate short-term predictions. The study[14] suggests a stock market price prediction model based on CNN-BiSLSTM. Its reference value for investments is limited, though, as it only forecasts the stock's closing price for the following trading day. The study's prediction timeline may be limited since investors like to forecast the stock's price and trend over a longer duration. The research[15] uses an LSTM-based approach to analyze and predict stock market movements. To enhance network weights and thresholds, the authors employ a self-adapting version of the PSO technique[16]. A prediction model for stock market opening prices based on the self-adapting variation PSO-Elman network is created after the optimized data, also known as the initial weight and threshold value, is fed into the Elman network for training. The investigation should concentrate on how effectively the model functions when faced with noisy or unpredictable data, even while its fault tolerance is covered.

2.1. State of the Art

To forecast the closing price of stocks from three distinct firms the following day, the authors[17] proposed machine learning models (KNN, RF, LR, and GB), which were evaluated using R2, RMSE, and MAE. The fact that the study[17] only looked at three businesses may have limited how far the results can be applied to other stock market companies. Predicting the daily price fluctuations of three significant equities that are traded on the Borsa Istanbul 100 index was the goal of the study[18]. The study[19] used financial data to generate new variables as inputs and Random Forest and Artificial Neural Network approaches to predict stock closing prices. The models were then assessed using RMSE and MAPE. Nevertheless, there isn't enough talk on the precise limitations of machine learning models. For stock closing price prediction, the approach put forth[20] uses RNNs, more especially LSTM models, in conjunction with technical indicators and stock data. Dimension reduction is accomplished by PCA, and optimization techniques such as Adam and Glorot uniform initialization are used. The tremendous volatility of the stock market makes it difficult to predict prices with any degree of accuracy. Machine learning techniques are used by the authors[21-22] to forecast the stock market. Regarding business sizes, both big and small businesses, the likelihood of financial market manipulation was the same in developed and emerging markets[25-29]. One important metric for identifying market manipulation is the biggest

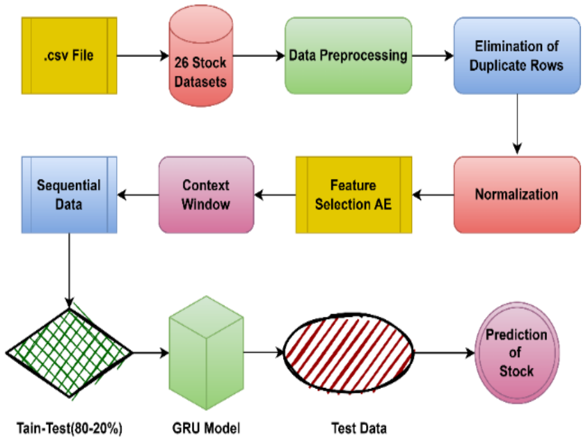

Fig. 1: Stock Market Forecasting Technique

price swing[30-31]. It can be challenging to discern between some acceptable trading practices and manipulators' illicit actions[32-33]. The author showed that a high number of false positives was the biggest surveillance problem[34]. Finally, the author[35] gave market regulators difficulties with resources and detection.

3. Methodology

Autoencoders and Gated Recurrent Units are an exclusive fusion architecture utilized in the development of this framework. It uses sophisticated mathematical modeling to analyze data in intricate ways. The following three sections make up our framework. The first is Dataset Formation, in which we compile information about the stock market from multiple datasets, followed by data preprocessing. In this second step, we use an autoencoder for feature selection, followed by the context window technique, to preprocess our data. Lastly, we create a deep learning model for the framework using a GRU-based approach, as shown in Figure 1 below.

3.1. Dataset Composition

Google's stock market data was gathered for this project from Kaggle, which is publicly available, and data from 25 companies was gathered from the NIFTY-50[23] Stock Market Data (2000-2021) Kaggle repository. There are 5303 data points in each dataset of the stock data. The information covers the period from January 1, 2000, to April 30, 2021.

3.2. Data Preprocessing

In time series data preparation, the context window method entails repeatedly dividing the data into fixed-sized windows depicted in Figure 2.

This technique helps to capture evolving patterns over time by generating segments that overlap or do not overlap, facilitating the examination of temporal dynamics and improving the precision of predictive modeling. The sequences are first stored in an empty list, and then the dataset is iterated through to extract consecutive data

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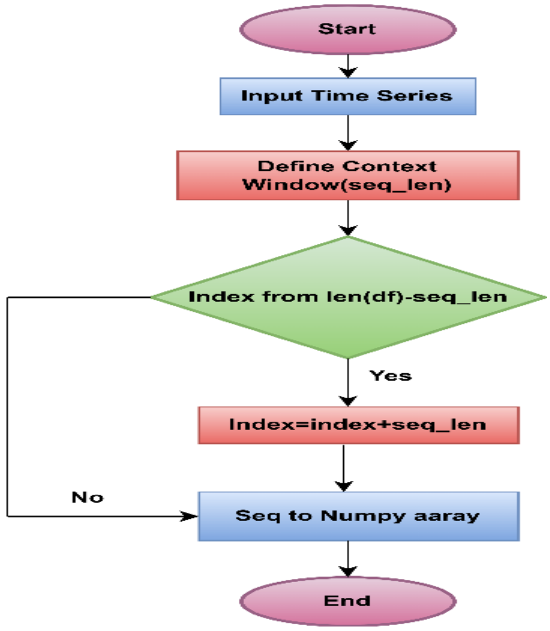

Fig. 2: An instance of the context window approach for GRU

segments of a given length, seq_len, and each segment is appended to the list. The range limit makes sure that only legitimate sequences are gathered while staying within the dataset's boundaries. The sequence list is then transformed into a NumPy array for efficient calculation. The array's shape is then printed to verify the number of features, length, and sequences. The context window technique is used in time series forecasting models to capture temporal dependencies in the data.

3.3. Model Design

We introduce a hybrid model based on AE-GRU for forecasting the stock market's future closing price and achieve a certain Mean Squared Error (MSE) of 0.001, Mean Absolute Error (MAE) of 0.021, and Max error of 0.213. Gated Recurrent Unit (GRU) is one sort of recurrent neural network (RNN) architecture intended to effectively handle sequential input. By tackling problems like vanishing gradients and long-term dependency learning, it was introduced to outperform conventional RNNs. Figure 3 explains the architecture of the GRU cell shown below. Normalized data is optimal for neural networks; the dataset values are scaled by the MinMaxScaler. The input layer with a shape equal to the number of original features is defined by the Autoencoder. This dense layer reduces the data's dimensionality from input_dim to encoding_dim. Activation function relu is used to ensure non-linearity, enhancing the model's ability to capture complex patterns. Reconstruction reconstructs the data back to its original shape, and a sigmoid activation function is used. Autoencoder extracts features directly from the encoded layer, and the optimizer Adam is used for efficient gradient descent updates. Autoencoder is trained using 100 epochs, which controls the number of training iterations, and batch

Table 2: Explanation of Symbols

Symbol	Meaning
Σ	Sigmoid activation function
Tanh	Hyperbolic tangent activation
Θ	Element-wise multiplication
Ꞔ$_t$	Resnet gate vector
Ŧ$_t$	Update the gate vector
$\bar{X}_t$:	Candidate hidden state
Ꭓ$_t$	Hidden state at time step t
ƀ$_t$	Input vector at time step t
W_p, W_q, W_r	Weight matrices for input ƀ$_t$
U_p, U_q, U_r	Weight matrices for the previous hidden state Ꭓ$_{t-1}$
c_p, c_q , c_r	Bias term

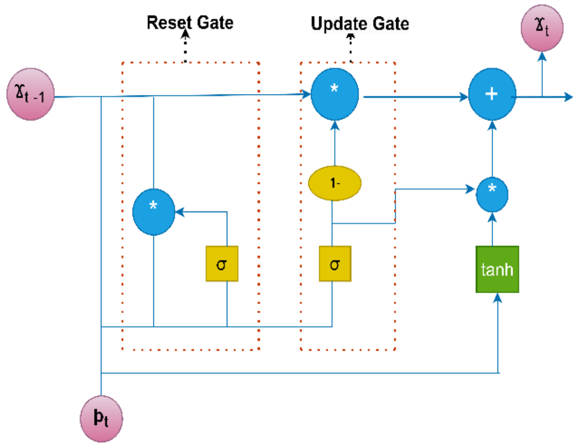

Fig. 3: GRU Cell Diagram

size 32 decides how many samples are handled at each gradient descent step. The extracted features are converted into a data frame for easy handling and analysis. GRU consists of an Update gate, a reset gate, a candidate hidden state, and a final hidden state. Furthermore, Table 2, shown below, explains the symbols used to form GRU.Table 3 above lists the shape, duplicate rows, and unique values having attributes close, open, high, low, and volume for 30 processed datasets.

Update Gate: The update gate identifies how much the prior hidden state should be preserved, and is represented in equation 1 below.

$$Ŧ_t=\sigma\ (W_p ƀ_t + U_p Ꭓ_{t-1} + c_p) \quad (1)$$

Reset Gate: The reset gate identifies the amount of the prior hidden state that should be forgotten and is represented in equation 2 below.

$$Ꞔt = \sigma\ (W_q\ ƀ_t + U_q\ Ꭓ_{t-1}+ cq) \quad (2)$$

Candidate Hidden State: The candidate's hidden state is a possible new memory and is represented in equation 3 below.

$$\bar{X}_t: = \tanh\ (W_r\ ƀ_t + Ur\ (Ꞔ_t\ \Theta\ Ꭓ_{t-10}) + c_r \quad (3)$$

Find Hidden State: The candidate's hidden state and the prior hidden state are combined to create the final hidden

Table 3: Unique values on 30 datasets of companies' stocks

Datasets	Shape	Duplicate Rows	Missing Values	Unique Values				
				Close	Open	High	Low	Volume
ADANIPORTS	2240,5	332	0	1311	1286	1322	1316	1798
WIPRO	2306,5	333	0	1341	1319	1350	1346	1824
ASIANPAINTS	2306,5	333	0	1341	1319	1350	1346	1824
BAJAJAUTO	2121,5	330	0	1292	1269	1307	1302	1703
KOTAKBANK	2306,5	333	0	1341	1319	1350	1346	1824
JSWSTEEL	2240,5	332	0	1311	1286	1322	1316	1798
BAJFINANCE	2306,5	333	0	1341	1319	1350	1346	1824
GOOGLE	2187,5	0	0	2154	2187	2187	2187	2120
BHARTIARTL	2306,5	333	0	1341	1319	1350	1346	1824
CIPLA	2306,5	333	0	1341	1319	1350	1346	1824
BPCL	2306,5	333	0	1341	1319	1350	1346	1824
BRITANNIA	2306,5	333	0	1341	1319	1350	1346	1824
GRASIM	2306,5	333	0	1341	1319	1350	1346	1824
COALINDIA	1506,5	328	0	956	935	961	963	1153
HCLTECH	2306,5	333	0	1341	1319	1350	1346	1824
DREDDY	2306,5	333	0	1341	1319	1350	1346	1824
HEROMOTOCO	2306,5	333	0	1341	1319	1350	1346	1824
HDFCBANK	2306,5	333	0	1341	1319	1350	1346	1824
HINDALCO	2306,5	333	0	1341	1319	1350	1346	1824
HINDUNILVR	2306,5	333	0	1341	1319	1350	1346	1824
ICICIBANK	2306,5	333	0	1341	1319	1350	1346	1824
INDUSINDBK	2306,5	333	0	1341	1319	1350	1346	1824
INFY	2306,5	333	0	1341	1319	1350	1346	1824
LT	2306,5	333	0	1341	1319	1350	1346	1824
ITC	2306,5	333	0	1341	1319	1350	1346	1824
IOC	2306,5	333	0	1341	1319	1350	1346	1824
ONGC	2306,5	333	0	1341	1319	1350	1346	1824
TECHM	2306,5	333	0	1341	1319	1350	1346	1824
TITAN	2306,5	333	0	1341	1319	1350	1346	1824
ULTRACEMCO	2306,5	333	0	1341	1319	1350	1346	1824

state, which is managed by the update gate and is represented in equation 4 below.

$$\mathfrak{X}_t = (1-\mathfrak{T}_t)\mathfrak{X}_{t-1} + \mathfrak{T}_t \, \Theta \, \bar{\mathfrak{X}}_t \quad (4)$$

4. Performance Analysis

Considering 30 stock market datasets, our model outperforms the others in forecasting the future closing price of the stock market, resulting in an average Max Error score of 0.213, an MAE of 0.021, and an MSE of 0.001, according to our analysis. To assess its performance, we evaluate our trained model on test data to see if it can accurately predict labels for previously unseen data. Table 4 offers compelling evidence of the robustness of the AE-GRU model in predicting stock market trends. The accuracy of the model's stock price predictions across multiple company datasets is shown in the provided performance metrics, comprising MSE, MAE, R2 score, and Max Error. The model successfully reduces prediction errors, as illustrated by the consistently low values of MSE and MAE and reliability in uncovering the latent structures within the data. Furthermore, the model accounts for a substantial portion of the variance in stock returns, evidenced by high R2 values across various datasets, reflecting fantastic out-of-sample performance and predictive ability. Besides that, the relatively low Max Error values indicate the model performs well despite the true value being different from the predicted value, hence its resistance to outliers and large stock price fluctuation. The model AE-GRU exhibits its versatility and efficacy in managing diverse market situations and company-specific trends by producing remarkable outcomes across many datasets. This performance consistency highlights the robustness of the model.

Furthermore, Stock Price Prediction on various datasets is

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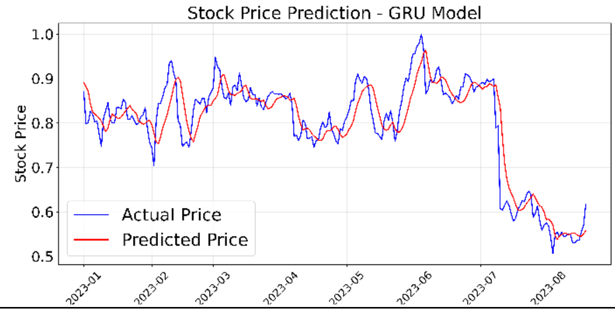
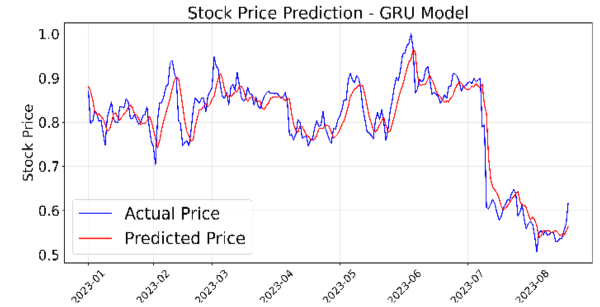
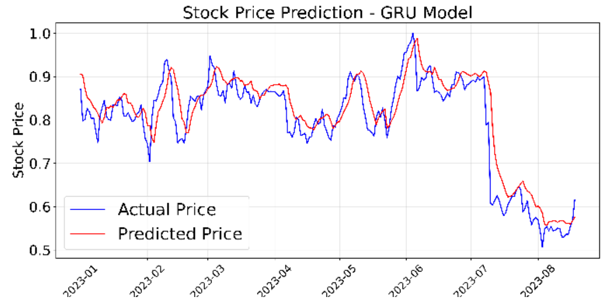


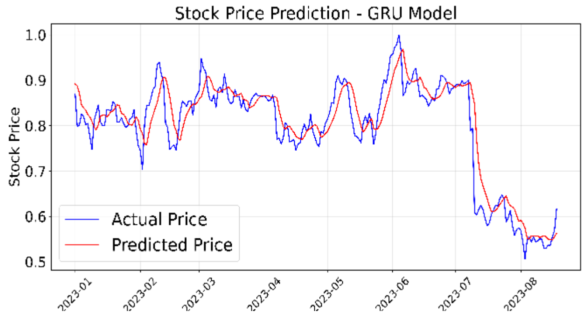
Stock Prediction on Asian Paints Dataset



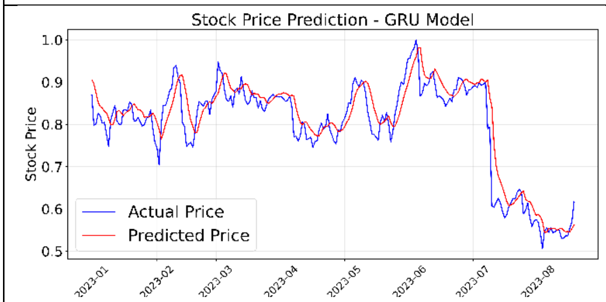
Stock Prediction on Bhartiartl Dataset



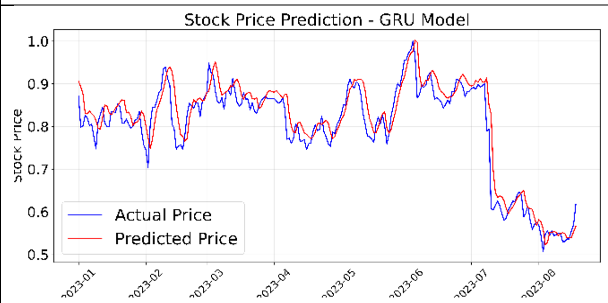
Stock Prediction on Cipla Dataset



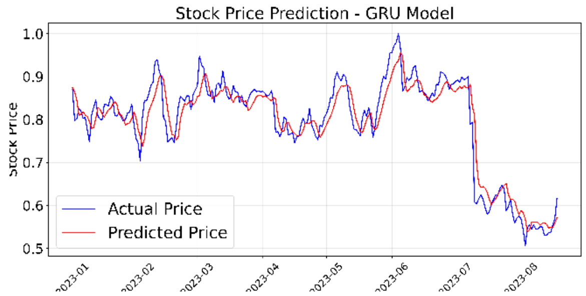
Stock Prediction on Hindalco Dataset



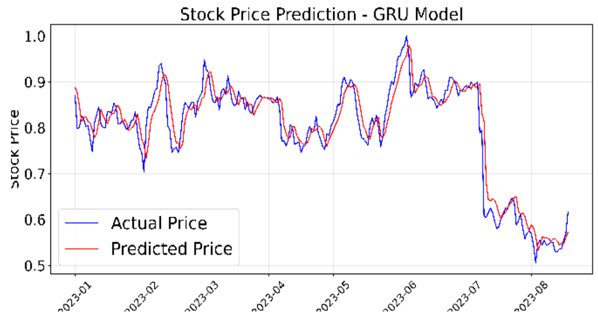
Stock Price Prediction on Indus Dataset



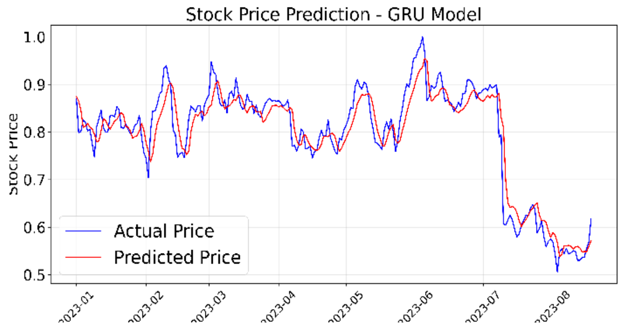
Stock Price Prediction on Kotak Dataset

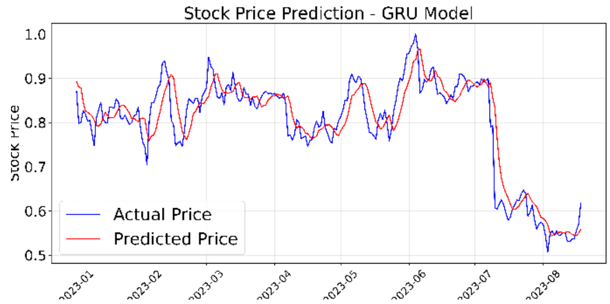


Stock Price Prediction on Wipro Dataset



Stock Price Prediction on ICICI Dataset





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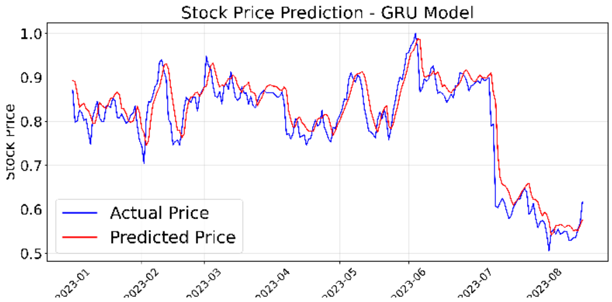
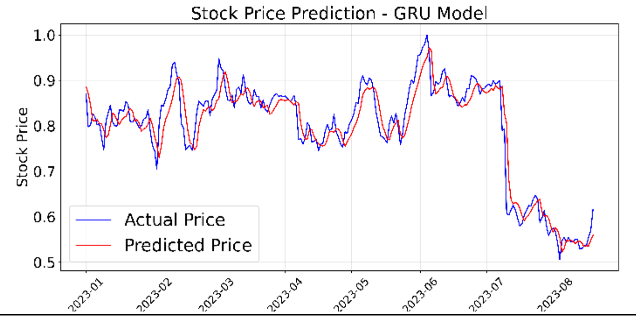
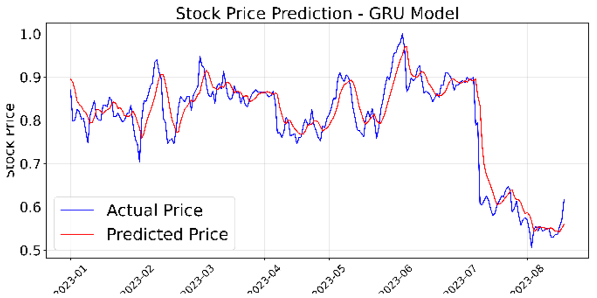
Stock Price Prediction on the HCL Dataset



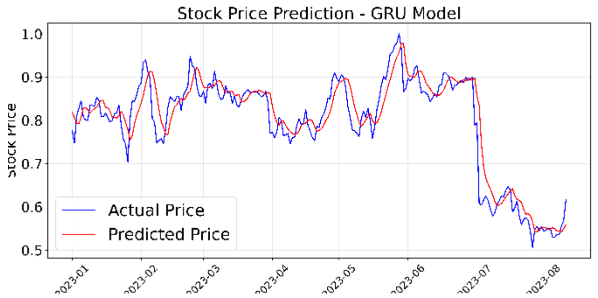
Stock Price Prediction on Dreedy Dataset



Stock Price Prediction on Britannia Dataset



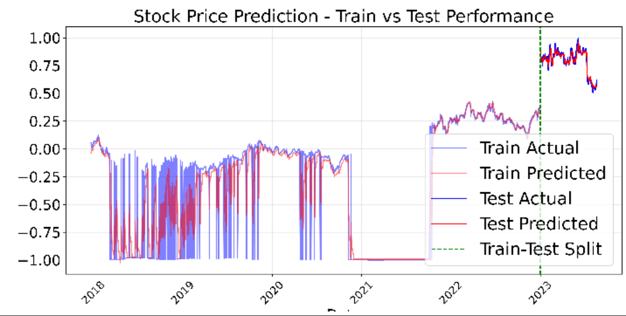
Stock Price Prediction on BPCL Dataset

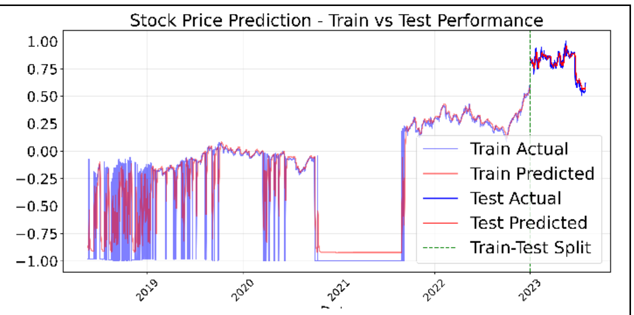


Stock Price Prediction on the LT Dataset

Stock Price Prediction on Bajaj Finance Dataset

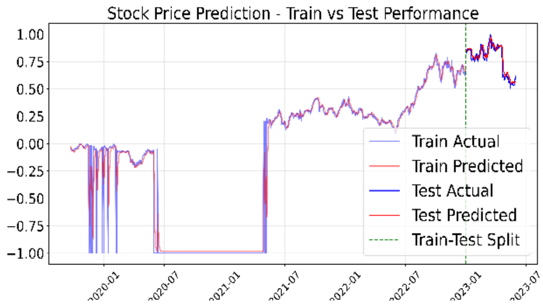
Fig. 4: Stock Price Prediction on Various Datasets

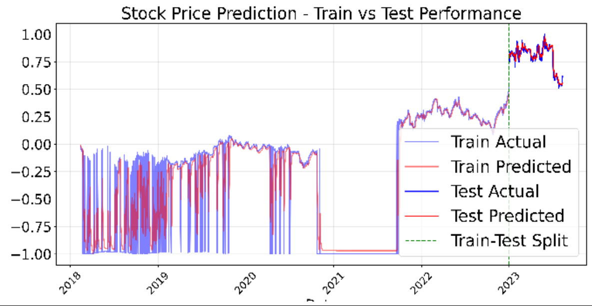




Stock Price Prediction on Adaniport Dataset

Stock Price Prediction on BajajAuto Dataset





Stock Price Prediction on CoalIndia Dataset

Stock Price Prediction on the JSWSteel Dataset

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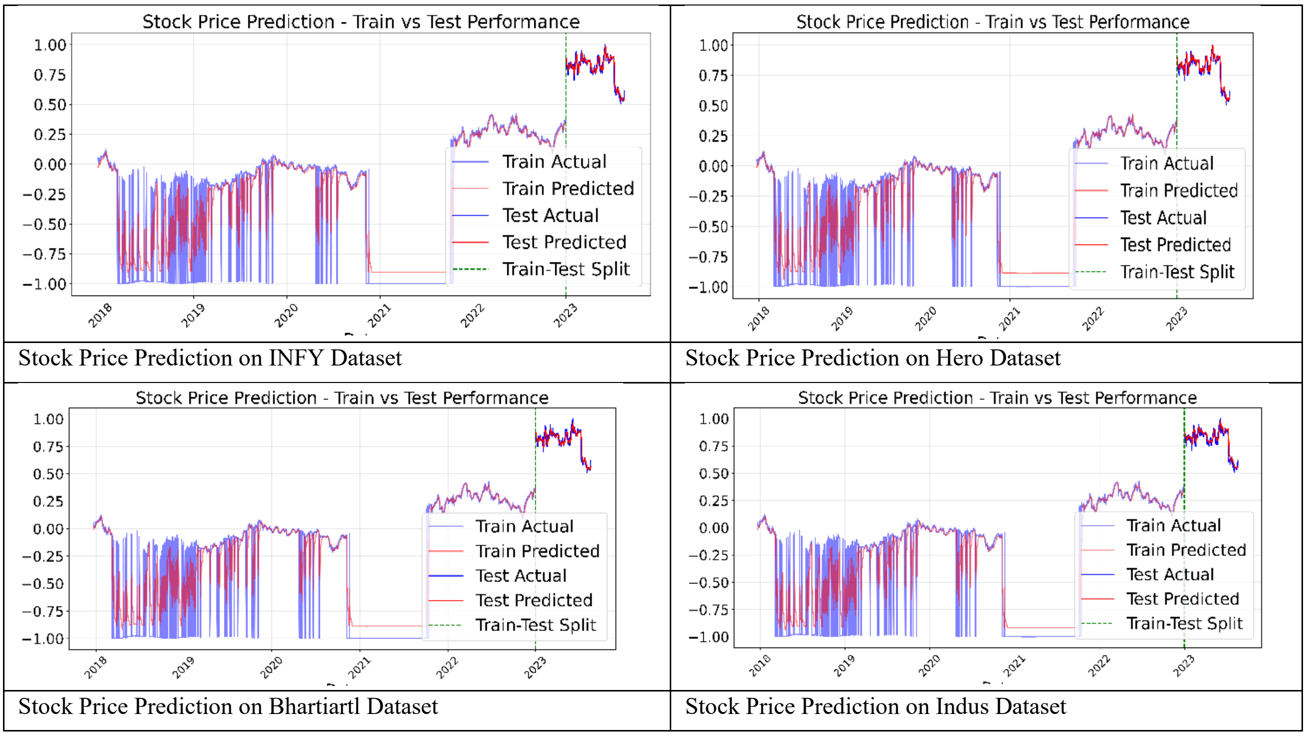

Stock Price Prediction on INFY Dataset | Stock Price Prediction on Hero Dataset

Stock Price Prediction on Bhartiartl Dataset | Stock Price Prediction on Indus Dataset

Fig. 5: Stock Price Prediction Train vs Test Performance on Various Datasets

Table 4: Evaluation of our model's performance using different datasets

Datasets	MSE	MAE	R2 Score	Max Error
ADANIPORTS	0.0012	0.0221	0.9060	0.225
WIPRO	0.001	0.022	0.9070	0.2200
ASIANPAINTS	0.0013	0.0221	0.9090	0.2287
BAJAJAUTO	0.0012	0.0221	0.9083	0.2026
KOTAKBANK	0.0013	0.022	0.9060	0.2140
JSWSTEEL	0.0012	0.0231	0.9060	0.2008
BAJFINANCE	0.0011	0.023	0.9072	0.2125
GOOGLE	0.0012	0.0223	0.9061	0.1817
BHARTIARTL	0.0013	0.02	0.9071	0.2189
CIPLA	0.0011	0.0215	0.9052	0.230
BPCL	0.0011	0.021	0.9042	0.212
BRITANNIA	0.0012	0.021	0.9070	0.225
GRASIM	0.0011	0.0213	0.9043	0.2093
COALINDIA	0.001	0.0202	0.9080	0.1581
HCLTECH	0.0012	0.021	0.9040	0.2125
DREDDY	0.0013	0.0223	0.9080	0.2099
HEROMOTOCO	0.0013	0.0221	0.9060	0.2225
HDFCBANK	0.0012	0.0222	0.9070	0.2170
HINDALCO	0.0012	0.0221	0.9030	0.2248
HINDUNILVR	0.0012	0.023	0.9042	0.2115
ICICIBANK	0.0013	0.0231	0.9091	0.2297
INDUSINDBK	0.0012	0.0223	0.9060	0.2147
INFY	0.0011	0.022	0.9092	0.1978
LT	0.0013	0.0222	0.9050	0.221
ITC	0.0013	0.023	0.9040	0.2296
IOC	0.0012	0.0221	0.9031	0.2177
ONGC	0.0011	0.0210	0.9092	0.2247
TECHM	0.001	0.0210	0.9021	0.1971
TITAN	0.0012	0.0210	0.9051	0.2085
ULTRACEMCO	0.0011	0.0210	0.9092	0.2247
Average	0.001	0.021	0.906	0.213

shown in Figure 4. Stock Price Prediction Train vs Test Performance on various datasets is shown in Figure 5.

4.1. Stock Price Prediction on Different Datasets Using AE-GRU Model

The stock price prediction using AE-GRU is performed on 30datasets to validate its performance. It illustrates the variation in performance between the actual and predicted prices. Some datasets, out of 30, are chosen, namely Bhartiartl, Cipla, Asian Paints, Indus, Hindalco, Kotak, Wipro, HCL, ICICI Bank, LT, Dreedy, and Bajaj Finance, to demonstrate the performance of the suggested model with respect to actual and predicted prices.

4.2. Stock Price Prediction Train Test Performance Using AE-GRU Model

The Stock prediction for various datasets, such as Adaniport, BajajAuto, CoalIndia, JSWSteel, INFY, Hero, Bhartiartl, and Indus, is chosen to perform train and test performance. The outcome of the train test performance illustrates that the model AE-GRU performs exceptionally well on the test datasets as well, indicating the suggested model's accuracy and robustness across multiple company datasets.

4.3. Comparison of Proposed Algorithm with Existing Ones

A comparative performance analysis of several neural network models utilized in earlier research to forecast stock market trends, specifically using the Asian Paint stock market dataset, along with an average of 26 datasets with an average of 30 datasets with the proposed one, is shown in Table 5. The proposed model minimized the MSE from 0.00428 to 0.0013, indicating better precision and reliable performance, diminish MAE from 0.0428 to 0.0221, thereby increases the model's resistance to anomalies, scale down R2 Score from 0.9095 to 0.9090 improving consistency in the model and lastly minimizing MaxError from 0.5185 to 0.2287 consequently improving model robustness. The proposed algorithm was able to reduce the Max error from 0.318 to 0.213, considering the average of 30 datasets, emphasizing the safeguards against extreme prediction failures. Figure 6 represents the comparison of the Asian Paint proposed model with the previously existing Asian Paint stock market parameters, thereby reducing the Max Error to a greater extent. The impressive performance, highest R2 score along with

Table 5: Performance Analysis of our model with Asian Paint's stock market datasets, and the LSTM-DNN Model

Model	MSE	MAE	Max Error
ASIANPAINTS[7)]	0.00428	0.0428	0.5185
ASIANPAINTS[14)]	0.00428	0.0428	0.5185
ASIANPAINTS (Proposed)	0.0013	0.0221 0	0.2287
LSTM-DNN[24)] (Average of 26 datasets)	0.001	0.021	0.318
Proposed (Average of 30 datasets)	0.001	0.021	0.2287

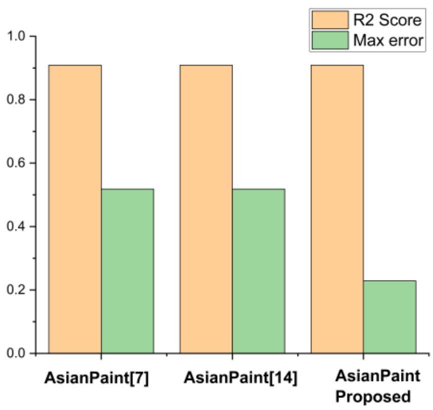

Fig. 6: A Comparison of the proposed model with the Asian Paint stock market

low MSE, MAE, paired with little deviation difference between actual stock prices and their predicted values from the model, shows the model's ability to generate accurate predictions, a core component to profitable trading decisions. Small values of Maximum Error indicate that the model is sensitive to outliers and increases the possibility of being profitable because of the model's responsibility to provide good predictions in dynamically changing market conditions. The accuracy, the stability of the forecasts issued, and the precision in choosing the forecast minimize the errors, showing that traders or analysts, who search for promising stock market possibilities, can be supported to gain valuable information by using this model.

4.4. Performance Metrics

We make use of Mean Squared Error, Maximum Error, R-squared score, and Mean Absolute Error as performance metrics. The mean absolute error (MAE) is an easy-to-understand measure, meaning how well the model can predict the stock price. MSE is an estimate of total variance and focuses more on larger values of error, and it has more weight on bigger differences from the actual and predicted value. The R2 score measures how well the model explains the variance of the stock prices. At the same time, forecasting accuracy's worst-case scenario is always shown (Maximum Error) and also emphasizes the potential outliers or the excessive errors that can be made. A popular metric for calculating the average squared difference between actual and anticipated values is the Mean Squared Error, or MSE. It is provided in equation 5:

$$\mathbf{MSE} = \frac{1}{n}\sum_{1}^{n}(y_i - \hat{y_i})^2 \quad (5)$$

where n is the number of observations, $y_i$represents the true value of the ith data point, and the anticipated value of the ith data point is represented by $\hat{y_i}$. Both positive and negative errors contribute equally when the errors are squared. The squaring operation penalizes larger errors more severely than smaller ones. Mean Absolute Error (MAE) is used to quantify the average size of errors between expected and actual data. MAE is less susceptible to significant errors or outliers since it uses the absolute difference rather than squaring the errors. It is provided in equation 6:

$$\mathbf{MAE} = \frac{1}{n}(y_i - \hat{y_i}) \quad (6)$$

MAE does not emphasize bigger deviations as MSE does; instead, it handles all errors equally. The coefficient of determination, or R2 score, evaluates how effectively a regression model accounts for the variance in the dependent variable, as represented in equation 7. It typically ranges from 0 to 1. However, R2 can be negative if the model performs worse than a straightforward mean-based model. Greater R2 values signify a better fit, which means that the model accounts for a larger portion of the

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variance in the target variable. When the model's R2 is 1, it accurately forecasts every real value. A model with an R2 of 0 is no more useful than merely taking the mean of the real values. Here, ü represents the mean of true values.

$$\text{MSE} = \frac{1}{n}\sum_{1}^{n}(y_i - \hat{y_i})^2 \quad (7)$$

$$QQ_{res} = \sum(y_i - \hat{y_i})^2 \quad (8)$$

$$QQ_{tot} = \sum(y_i - \text{ü})^2 \quad (9)$$

AE-GRU proposed a model with a complex model structure that effectively deals with market volatility and the complexity of stock market prediction patterns. Notably, the GRU in the model is crucial in recognizing and preserving long-term dependencies in the data, and retaining important data without forgetting it for a long time. This ability is exceptionally beneficial if there are sudden and noticeable market movements. The model can quickly learn and adapt to these uncertain market conditions, making better predictions as things change fast. Moreover, as discussed in Section III, the Autoencoder part of the model can be very good at identifying complex patterns in the data, including complicated patterns and relationships that may not be seen at the surface level. This capability is needed to handle diverse patterns in stock market data, which are influenced by several variables and cause price movements.

The model uncovers hidden relationships that utilize the autoencoder component to analyze large datasets, extract crucial features, and leverage complex patterns for more accurate forecasts. Furthermore, the hybrid model enhances predictive capabilities by merging the strengths of both methodologies, AE and GRU architectures. The model understands temporal and long-term dynamics, enabling it to accurately capture market volatility and complex patterns from real firm stock data. This unique combination results in more precise and reliable stock market forecasts. By adapting to changing market conditions, the model identifies intricate patterns in the data and generates informed predictions considering the complexities of stock market dynamics.

5. Discussions & Limitations

A robust method to tackle the challenging issues related to forecasting the stock market movement is obtained by the AE-GRU model. This architecture combines the benefits of GRU networks, famous for learning sequential regularities and temporal relationships throughout time, with autoencoders, which are good at discerning complex regularities and attributes within large datasets. The information about the stock market is inherently nonlinear and influenced by several factors, such as geopolitical happenings, sentiment in the market, and economic indicators. They can capture and store long-range dependencies in sequence data, and a particular task fits quite well. By recognizing subtle patterns and seasonal patterns in stock prices, the model can make more accurate forecasts and provide useful knowledge on price patterns in the market. It shows its strong performance over 30 real-world firm datasets by achieving 0.9061 average R-squared (R2), 0.021 Mean Absolute Error (MAE), and 0.001 Mean Squared Error (MSE) average scores. These results indicate that the model is reliable and effectively handles different market situations and types of datasets. Furthermore, the AE-GRU model alleviates the critical issues observed in other studies. Unlike earlier methods, which often struggle with noisy data or cannot learn long-term trends, this hybrid approach emphasizes robust data handling methodology and extends the predictive horizon. The model exhibits excellent generalization and performance stability across multiple stocks and market states.

We have acknowledged some limitations of our hybrid architecture, which is built based on the GRU Autoencoder models, even if the results are promising. Despite the model's substantial robustness on diverse datasets, the quality and granularity of the input data could influence the model's performance. As market data may contain anomalies, like missed numbers, inaccurate financial reports, or incomplete historical data, they can all adversely affect the predicted accuracy of the model. Data quality is the most important aspect in financial markets. The lack of quality within the data sources may cause gaps in data collection, misprints in financial statements, and delayed information. The model's skill at making accurate predictions may be compromised if such issues are present. Furthermore, the granularity of the data is also very crucial. Model-driven differences might be found if the model is employed but not learned on the training set. In summary, our method demonstrates high potential and robustness for various applications, and the granularity and quality of the input data should be considered in detail.

6. Conclusion and Future Work

The proposed research presents a significant advancement in financial analytics by achieving enhanced stock market prediction with a hybrid AE-GRU-based fusion architecture. The analysis has also exhibited remarkable flexibility and consistency across diverse datasets and idiosyncratic patterns involving the organization. It has proven its correctness, variance prediction, fit, and outlier tolerance through in-depth analysis using criteria such as MAE, MSE, R2 Score, and Maximum Error, indicating that the model prediction of stock price is of high performance. In line with the limitations of prior research, the study extends the prediction horizon to cover longer-term trends and presents a deeper level of insight to traders and investors. The research also highlights the model’s aptness to guide shrewd investment decisions during the ebbs and flows of market trends, with its excellent prediction accuracy compared to existing neural-network-based methods being demonstrated. The paper contributes to the forecasts in finance by showing the flexibility, stability, and potential of the model in stock market prediction. Limitations of the proposed architecture are anomalies in market data, erroneous financial reports, and inconsistent historical records that badly diminish the expected accuracy of the model. The correctness of the data obtained is a great factor; therefore, discrepancies in data must be avoided to have an accurate forecast.

Significant steps are involved in implementing the proposed model's adaptive learning and real-time prediction features. Firstly, integrating live data streams from money data sources and handling incoming market info well will be ensured using a design that reacts to events. Real-time tidying up and making things standard will be possible with building a strong way to get ready data. Fast predictions will be possible by placing the model on flexible platforms like AWS SageMaker, helped by ways to make it better, like speeding up with hardware and making the model smaller. Keeping high predicted correctness will be helped by automatic retraining steps and continuous monitoring of performance measures.

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