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Predicting Daily Stock Market Price using a Few-shot and Modified Transfer Learning

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Abstract: Predicting the stock market and future stock prices is a difficult task. Stock customers have a strong requirement for market estimation. However, it frequently fails to produce successful results when predicting the stock price using a small amount of previous data. The Adaptive Deep ResNet with Few-Shot Learning deep model, which is new and built on transfer learning and Few-shot learning, is used in this research (APR-FSL). This work aims to maximize stock market price prediction performance, which presently offers predictions with the highest accuracy and lowest error rates. The proposed methodology focused on enhancing stock market prediction by fusing a Few-shot learning and knowledge transfer from transfer learning. Experiment results on the huge stock market dataset showed that the APR-FSL model outperforms other existing methods in terms of accuracy.

Keywords: *methods, performance, requirement, APR-FSL*

1. Introduction

The stock exchange is a platform that connects many exchanges and markets through a regular process of buying and selling items that are released as publicly traded shares. On this platform, a variety of situational financial functions were carried out for formal trade processes according to predetermined rules and guidelines. A country may have a variety of stock exchanges where transactions on stocks can be made. The stock market definition uses two different terms: stock exchange and the stock market with consideration of formal trading assets. If someone participates in the stock market, they have dubbed stock market traders since they buy and sell shares of various stocks [1].

Predicting the stock market price is a constant struggle for many business experts and researchers. Financial markets, one of humanity's most fascinating discoveries, have a tremendous impact on the national economy [2]. Stock trading has gained popularity in recent years, owing largely to technological advancements. Investors look for methods and techniques that will boost profits while decreasing risk.

To maximize earnings, investors must estimate the companies' future stock value. To create reliable stock market predictions, several prediction systems have been developed. The forecast of stock market prices is an intriguing and difficult academic topic [3].

Because of extrinsic elements such as social, psychological, political, and economic effects, predicting the stock market with higher precision is extremely difficult. If investors do not have sufficient experience and skills in their investment, they may incur a significant loss. The same charts can yield different results to individual economic expertsThe system input should favour technical analysis data over fundamental analysis data. Both short-term and long-term analyses are done using technical analysis.

Making the proper decision on time has presented a lot of obstacles since anticipating the movement of the stock market price requires a big amount of information. This knowledge is critical for investors because stock market volatility can result in a significant loss of investment. The analysis of this huge amount of information is thus valuable for investors, as well as for determining the direction of stock market indices [4]. With the tremendous success of Machine Learning (ML) in many domains, research on ML in finance has received more interest and is being investigated continually.

However, the main principle of both conventional ML methods and deep learning models is that training and test data are independent. To ensure the model's accuracy and stability, it must also have the same distribution and require a sizable amount of training data. To adhere to the fundamental presumption of the same distribution in the successful development of stock price forecasting, previous research usually used historical data exclusively for the future trend prediction of its stock price.

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The ultimate goal of the work is to improve stock market price prediction by implementing transfer learning and Few-shot learning, which is also known as low-shot learning that forecasts next day stock market in a target task given a few labeled data, where data in the target task are not given in a training phase. However, very little data cannot be used for model training when you come across companies with inadequate historical data. so, transfer learning is employed in the training phase as a source dataset for the stock price prediction.

The proposed work's important contribution is

- ❖ To address the issue of insufficient training data and pre-trained models and to shorten the training convergence time, the transfer learning approach and few-shot learning are applied.
- ❖ Transfer learning acts as a feature extractor and an additional dropout layer is employed to overcome the overfitting problem.
- ❖ To enhance the efficiency of the system and to forecast future values with maximized prediction performance of the model with less error.

2. Literature Survey

A deep learning-based model was proposed by Ding *et al.* [5] by utilizing Recurrent Neural Network and Long Short-Term Memory (RNN-LSTM). The proposed network model automatically predicts the stock's opening, lowest, and peak prices using LSTM and deep RNN. The experiments result indicated that the related model predicts multiple values with a prediction accuracy of higher than 95%, outperforming the other two models.

Using data from financial news databases and Harvard IV-4, Minh *et al.* [6] created a novel two-stream-based gated recurrent unit network with an embedding algorithm. The result showed that: 1) a two-stream Gated Recurrent Unit (GRU) outperforms state-of-the-art models; 2) Stock2Vec is more effective at dealing with financial datasets, and 3) an experimental scenario using the proposed model demonstrated that the presented method is successful for stock prediction. The TGRU model outperformed the LSTM and GRU models.

Shah *et al*. [7] recommended a system based on a convolutional neural network (CNN) coupled with LSTM for predicting the closing price of stock market data. Using a proposed model and time series modeling with a look-up length of 20 trading days, it is possible to predict the movement of the next day. Based on 10 years of data, this model can reliably anticipate the target variable and closing price with a mean absolute percentage error of 2.54%. The recommended approach significantly outperformed the conventional purchase-and-hold strategy in terms of return.

The stock sequence array convolutional LSTM (SACLSTM) technique was developed by Wu *et al.* [8]. It created a sequence array from previous data and related economic trends. Then, the input images are passed in the form of an array to the CNN technique. The trial data consists of ten stocks from Taiwan and the United States. The convolutional layer and pooling layer were then utilized to extract specific feature vectors, and these vectors served as the input vector for the LSTM. When compared directly to more traditional methodologies, the forecasting effectiveness of the proposed algorithm in this study resulted in superior outcomes.

To address the issue of time-series data during feature extraction and price movement prediction, Wu *et al.* [9] propose a novel convolutional revolutionary neural network that may be viewed as a system for increasing stock trading prediction accuracy. The proposed method is known as SSACNN, which stands for simplified sequence array convolutional neural network. To accept an array as the input graph for the convolutional neural network framework, SSACNN gathers data such as previous as well as present stock market prices. The result of the study revealed that SSACNN's motion prediction performance had significantly improved, indicating that it may be used in the real financial market. Five Taiwanese and American stocks were selected for comparison with the aforementioned algorithms.

Nabipour *et al.* [10] focused on the stock market group's future predictions. From the Tehran Stock Exchange financials, petroleum, non-metallic minerals, and basic metals are the four groups named diversified were selected for experimental evaluations. Each of the prediction models' inputs was given ten technical indicators. LSTM demonstrated more accurate findings with the best model-fitting capabilities of all the algorithms utilized in this work. Furthermore, Adaboost, Gradient Boosting, and XGBoost are typically formidable competitors for tree-based models.

Pang *et al.* [11] proposed the first model by combining LSTM and an automated encoder. and a second model which is based on deep LSTM with an embedded layer to predict the stock market. In those two models, the input was vectorized using the embedding layer and the automated encoder to forecast the stock using an LSTM neural network. According to the results obtained from the experiments, the proposed second model is superior to other models.

Kelotra and Pandey [12] proposed the Rider-MBO approach, which combined the Rider Optimization

Algorithm (ROA) and the Monarch Butterfly Optimization (MBO). Records from the livestock market are first processed to provide technical indicators that reflect features. Following feature selection, these features are clustered using Sparse-Fuzzy C-Means (Sparse-FCM). The Deep-ConvLSTM model includes substantial features that allow for effective forecasting. Data from the livestock market is first processed to provide technical indicators that reflect characteristics. Following feature selection, these features are clustered using the Sparse-Fuzzy C-Means algorithm (Sparse-FCM).

As the most crucial stage of the CNN computational technique, Chung *et al.* [13] focused on the feature extraction stage of CNN optimization. The CNN model's parameters were systematically optimized using a Genetic Algorithm (GA) in this study. They evaluated the model's efficacy by comparing prediction results to those of traditional models. The result showed that the GA-CNN outperformed the comparison models, confirming the viability of the hybrid GA-CNN technique.

To forecast the stock market data, Nti *et al.* [14] developed a GASVM model based on a support vector machine (SVM) and a Genetic Algorithm (GA) for selecting features from the input data and optimizing the kernel parameters of SVM. In this study, GA was used simultaneously to optimize the various SVM model parameters. The proposed model attained a high accuracy when compared to Random Forest, Decision Tree, and Neural Network. As a result of the preceding, it is reasonable to conclude that the recommended (GASVM) technique provides a suitable strategy for feature selection and parameter optimization of various SVM model components, hence removing the requirement for time-consuming parameter optimization.

IKN-ConvLSTM, a unique multi-source information-fusion stock price prediction system based on hybrid deep neural network (CNN and LSTM) architecture, was proposed by Nti *et al.* [15]. The empirical evaluation of this method was carried out using stock data from Ghana Stock Exchange (GSE). The combined dataset beat the separate dataset in terms of prediction accuracy, specificity, sensitivity, and F-score. According to the study's findings, combining many stock price indicators into a single data form leads to higher forecast accuracy than independent data sources for prediction.

3. Materials and Methods

3.1 Method Outline

The proposed approach for forecasting the next day's stock market price is detailed in this section. Figure 1 depicts an overview of the proposed research. This work employs two datasets: the source dataset and the target dataset. The source data is utilized to pre-train the model, while the target dataset is used for new tasks. The source dataset (huge data) we considered is an exchange-traded fund (ETF). It is pre-processed and given to a pre-trained model during training.

A pre-trained model based on transfer learning called ResNet-50 is used. Fine-tuning is done after the model has been pre-trained to increase the model's performance. Then the prediction is carried out using a new dataset which is a query and support set based on fine-tuned results. This dataset is given additional layers to test the model for predicting US stocks.

3.2 Dataset

Huge Stock Market Dataset, which is openly accessible for research, was used in this work. This database comprises daily market price and volume data for US and ETFs traded on the New York Stock Exchange (NYSE), the National Association of Securities Dealers Automated Quotations (NASDAQ), and the New York Stock Exchange located in New York City (NYSE MKT) [16].

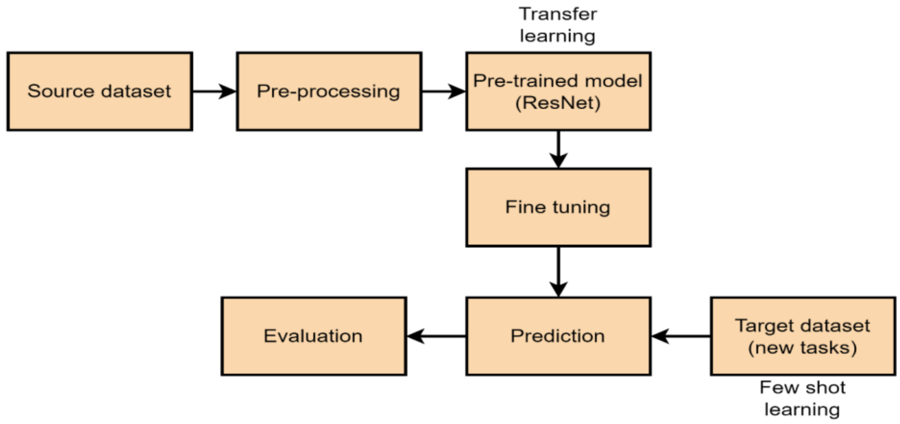

Fig 1 Overview of the proposed work

3.3 Data Reduction/Pre-processing

The utilized dataset contains structured data tables for (Date, Open, High, Low, Close, Volume, and OpenInt). Excel format was used to convert the data from CSV format. Following that, missing values were taken out of the dataset. Empty rows and other rows without data are eliminated from the dataset. This dataset underwent more cleaning before being applied to prediction.

3.4 Adaptive Deep ResNet with Few-shot learning (APR-FSL)

A novel deep learning model named Adaptive Deep ResNet with Few-shot learning (APR-FSL) is proposed to predict the daily stock market for new or target tasks based on transfer learning & Few-shot learning.We focused on enhancing stock market forecasting in this work via combining few-shot learning and knowledge transfer from transfer learning. The proposed work's architecture is illustrated in Figure 2.

The ResNet-50 modified model is a different version of the ResNet-50 model. It retains the feature extractor and fully connected layer as its basic layers (frozen layers) but adds new layers including dropout, Rectified Linear Unit activation layer (ReLU), and SoftMax.

The application of knowledge acquired from solving one problem to another that is similar to it is known as transfer learning. An image classification model based on ResNet-50 was chosen because ResNet has demonstrated remarkable performance in recent years.

The general technique for transfer learning is to first train a deep neural network ResNet-50 on a big data set, then finetune the model on a smaller data set. In other words, it establishes a connection between the original dataset and the new datasets, frequently by extracting the functional relationship, which may then be used as a new data feature in the generalization method. Finally, the new data are fed into the generalized model, which is then used to develop a specialized model for transfer learning based on the given transfer relationship. Pretraining allows us to find the best initial weights for target task learning.

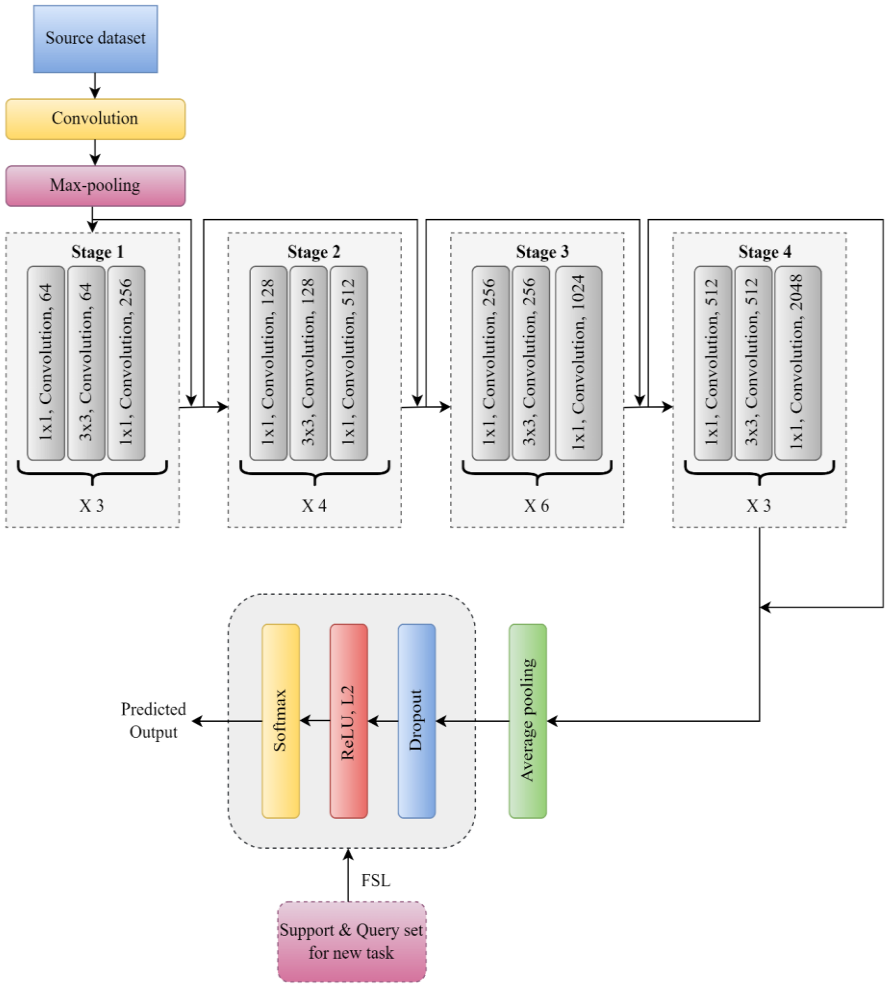

Fig 2 Architecture of the proposed APR-FSL model

Transfer learning has various advantages [17] (1) It vastly improves the efficacy of few-shot learning. Training with a significant amount of existing data yields the initial generalization model effectively lowers the cost of training a Few-shot learning algorithm. (2) Transfer learning can aid in resolving some of the difficulties associated with feature extraction in small samples. A suitable reference feature set for the Few-shot dataset can be obtained by training the generalization model. (3) Transfer learning effectively improves Few-shot learning generalization learning power. Few-shot learning efficiently avoids overfitting by learning the relatively rich properties of current datasets.

In this work, first ResNet-50 is trained on the ETF data and then fine-tuned with new data for predicting new stocks. Instead of layers, this network uses layer mapping. This type of mapping is referred to as residual mapping. The ResNet-50 avoids the gradient vanishing problem by employing residual units. Let a and b represent the input and output vectors of the layers.Assume $H(a)$be a stacked nonlinear layers function. The residual function is stated as,

$$F(a) = H(a) - a \quad (1)$$

So, $H(a) = F(a) + a$ can be yielded as a residual function, where stacked nonlinear layers are represented by F(a) and a. The benefit of the proposed approach is that it eliminates the vanishing/exploding gradient problem by automatically bypassing any layer that impairs the architecture's performance.

The ResNet50 model is easy to train and has a lot of benefits, including the potential to do residual learning directly from images instead of image characteristics [18]. As a result, before training the model, the features do not need to be extracted.

The residual block is defined in the below equation [19],

$$b = F(a, \{W_a\}) + a \quad (2)$$

where F denotes residual mapping to be learned and W_a denotes weight in the weight matrix.

The 50-layer residual network used in the standard pre-trained ResNet-50 was trained using the ImageNet dataset. The 2D time-frequency diagram used in this study was created from time series stock market data, and they differed greatly from the images in ImageNet. As a result, the fully connected layer and the last layer of the pre-trained ResNet-50 were modified to enable prediction using the updated ResNet-50. The ResNet-50 was then retrained to generate the changed parameters.

3.5 Convolutional layer

The convolution procedure is performed in a convolutional layer. Convolution is the process of applying filters to nearby data points and sending the outputs to another layerThe input matrix is multiplied by a fundamental matrix that has two essential properties: weights and form. The model learns the weights while training and the shape represent the filter's coverage.

3.6 Pooling layer

The pooling layer subsamples the data. The size and the cost of computing are both reduced through pooling. Following the convolutional layer's production, the pooling gathers the data and outputs it based on the pooling type selected.

3.7 Few-shot learning

The Few-shot learning for forecasting stock market data work divides the dataset into three categories such as training dataset, support set (S), as well as query sets (Q). For pre-training the network, the training data is derived from a different sample space during the training phase. These types seem to be mutually exclusive when compared with support as well as query sets. The support and query sets' sample categories are identical, yet each set's samples are mutually exclusive. The support set contains very few samples, it is utilized to train the network during the test phase. After the model has been trained using the support set, the efficiency of the proposed model can be evaluated with a query test for the new class type. In the event of a failure, the model's learning potential is limited because the support set has fewer samples than the training set and the sample categories are absent. A limited number of samples can be examined.

Few-shot learning approach can be known as an N-scheme K-shot problem. If every support set comprises N classes of samples, then every class contains K number of samples. Similarly, the underlying problem in few-shot learning is an N-scheme K-shot problem. In this, the selection of N classes was done from the training dataset during every training episode. Also, for replicating the support set, samples from the training dataset were considered from every type of N class. For the remaining N class samples, choose C samples at random (as the query set). Until the model becomes convergent, repeated training will be carried out for the stated dataset during training.

3.8 Additional layers

As discussed before, along with transfer learning, Few-shot learning is used during prediction. The APR-FSL model acquires knowledge from a pre-trained baseline model and a few-sort learning process. Overall, both are used for predicting the daily stock market price in the following layers.

Dropout: A dropout layer with a 50% chance of dropping out is one of the additional layers in the model. This decreases overfitting by randomly dropping 50% of the parameters. Dropout is a popular strategy for dealing with overfitting in a neural network by turning off some of the neurons, pushing the model to learn successfully with only a subset of the neurons. The proportion of dormant neurons in a dense layer is one indicator of dropout. Because certain neurons may be inactive at random throughout each epoch, this model relies on the others to train effectively and aid in generalization.

ReLU activation layer and softmax layer: A Rectified Linear Unit (ReLU) activation layer with L2 regularisation and ridge regression come next after this dropout layer. The regularisation parameter has a value of 0.02. Regularization, which involves combining a penalty with the cost function, is necessary to prevent the overfitting of the model. A softmax activation layer with L2 regularisation (regularisation parameter: 0.02) is the last step.

The weights were optimized during training using the stochastic gradient descent (SGD) optimization approach with a mini-batch size of 64. The learning rate and the maximum number of epochs are adjusted to 0.0001 and 50, respectively, after fine-tuning the deep learning settings to verify that the whole data set was included for optimal training. The loss function is binary cross-entropy. The hyperparameter of ResNet50 is tabulated in Table 1.

Table 1 Hyperparameter values of ResNet50

Hyperparameters	**ResNet50**
Initial Learning rate	0.0001
Batch size	64
Dropout	1
Activation function	ReLU, Softmax
Epochs	50

4. Result and Discussion

For stock market prediction in the proposed APR-FSL model, a sizable stock market dataset is employed. A total of 70% of the dataset is utilized for training, while 30% is used for validations. Accuracy is one of the crucial indicators for forecasting stock exchange predictions. The metrics mean absolute error (MAE) and mean square error (MSE) are used to calculate the deviations of actual and deviated values (MSE).

4.1 Performance metrics

❖ **Accuracy**

The degree to which measurements are accurate concerning a target or reference value. To put it another way, accuracy is a number that expresses how well a model predicts a price movement in the stock market that matches the actual price movement on a stock exchange. The accuracy value is evaluated and compared with existing methods and is tabulated in Table 2. The accuracy is calculated as,

$$Accuracy = \frac{TP+TN}{TP+FN+TN+FP} \quad (3)$$

Table 2 Comparison of Accuracy value

Model	**Accuracy** %
MALSTM-CNN [20]	77.48
GASVM [15]	93.70
MR model [21]	94.00
APR-FSL model	96.50

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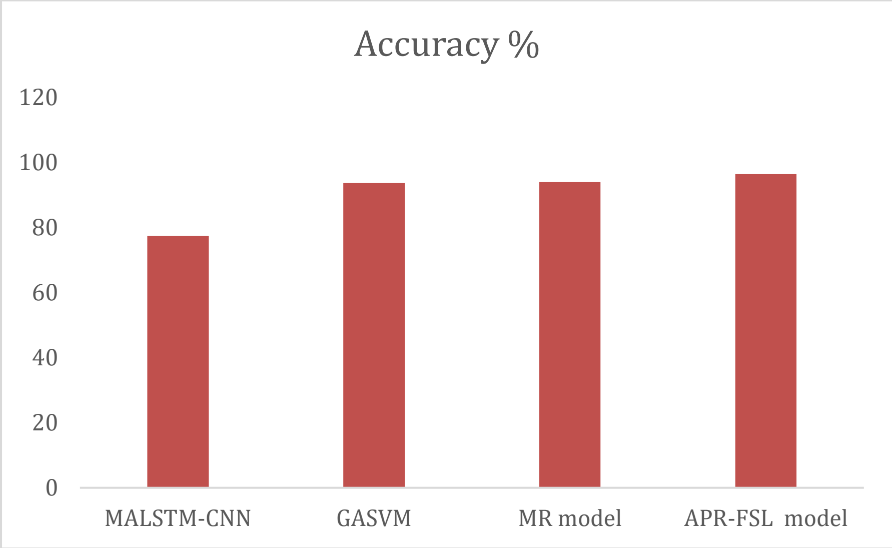

Fig 3 Comparison of accuracy value

Figure 3 clearly showed how the proposed APR-FSL model is compared to previous stock prediction market techniques, as well as how far superior the proposed algorithm is to typical neural network prediction and the rest of the deep learning methods.

❖ **Mean Absolute Error (MAE)**

The mean absolute error is calculated by taking the absolute difference between the actual and predicted values in the dataset. The mean of the dataset residuals is computed. The actual state of the expected value error is described by the absolute error average (MAE).

$$MAE = \frac{1}{N}\sum_{i=1}^{N} \quad |y_i - \hat{y}| \tag{4}$$

❖ **Root Mean Squared Error (MSE)**

Finding ultimately minimized errors in anticipated values is done using RMSE. This statistic displays the typical magnitude of the estimated inaccuracy in the value that was anticipated.

$$RMSE = \sqrt{MSE} = \frac{1}{n}\sum_{1=t}^{n} \quad e_t^2 \tag{5}$$

Table 3 Comparison of MAE and RMSE value

Classification Method	**Mean Absolute Error (MAE)**	**Root Mean Squared Error (RMSE)**
Linear regression [22]	1.33	1.58
AG-LSTM [23]	0.5616	0.6413
APR-FSLmodel	0.1230	0.2151

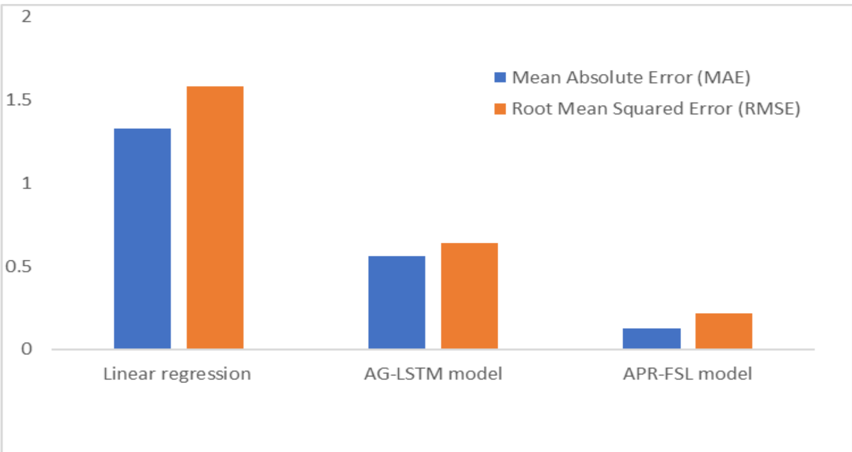

Fig 4 Comparison of MAE and RMSE Value

Table 3 compares the suggested approach MAE and RMSE error levels and Figure 4 demonstrates that the suggested framework surpasses the prior model in terms of MAE and RMSE, with values of 0.1230 and 0.2151, respectively. It reduces the network's training time while also assisting the prediction model in effectively predicting the data. Therefore, the APR-FSL Model demonstrated its ability to accurately forecast future stock price fluctuations daily.

5. Conclusion

Forecasting stock prices is challenging due to the stock market's noisy, volatile, and nonlinear data. The process of attempting to estimate the future value of a company's stocks or similar financial instruments traded on an exchange is known as a stock market prediction. Accurate stock market price forecasting aids investors in increasing their profit in the financial market. In the proposed model, modified ResNet-50 is a pre-trained model based on transfer learning is used and pre-trained data is collected from the Huge Stock Market Dataset.The evaluation results showed that the proposed APR-FSL method outperforms the other baseline models in stock market forecasting, with a 96.50% accuracy. The metrics used for evaluation are an MAE value of 0.1230, and an RMSE value of 0.2151 which shows that the proposed integrated system has satisfactory prediction performance.

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