DIGITAL INVESTMENT PREDICTION IN CRYPTOCURRENCY

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Abstract: Bitcoin is a digital currency (cryptocurrency) that is used for digital payment, exchange, and investment purposes all over the world. Bitcoin is a decentralized good, meaning that no one owns it. Bitcoin has always been based on the immutable blockchain concept. Bitcoin transactions are simple because they are not tied to any country. Different marketplaces are known as "bitcoin exchanges" are available for investment. These enable people to own and trade Bitcoins in a variety of currencies. Mt Gox is the most well-known Bitcoin exchange. Bitcoins are stored in a digital wallet, which functions similarly to a bank account. A place called Blockchain stores the history or record of all transactions as well as the timestamp data. A block is a single record in a blockchain. Each block has a reference to the previous data block. On the blockchain, all data is encrypted at all times. The value of Bitcoin fluctuates similarly to that of a stock, but in a different way. For stock market price prediction, enormous algorithms are used. The factors that influence Bitcoin, on the other hand, are distinct. As a result, predicting the value of Bitcoin is critical to making informed investment decisions. Unlike the stock market, the value of Bitcoin is unaffected by economic events or government intervention. As a result, we believe that forecasting the value of a single bitcoin is essential. Cryptocurrency (Bitcoin) is gaining popularity in this decade and is proving to be a lucrative investment for traders. Bitcoin's price fluctuates, unlike stocks or other foreign exchanges, because it trades 24 hours a day, seven days a week. Traders and investors need a way to accurately predict the Bitcoin price trend to reduce risk and increase capital gain. Many previous works on cryptocurrency value prediction have had lower accuracy and have not been cross-validated.

Keywords: RNN(Recurrent Neural Network), Minmax Scaling, LSTM(Long Short-Term Memory), BTC[CAD].

1. Introduction

Because of advancements in financial technology, a new type of asset known as cryptocurrency has emerged, as well as a significant research opportunity. Price volatility and dynamism are so numerous, that forecasting cryptocurrency value is a complicated process. Hundreds of thousands of cryptocurrencies are in use across the globe. Bitcoin has recently become a household pet due to its incredible growth, unpredictable irregularity, and engaging applications. While the cryptocurrency market is still unproven and untested as a viable currency, it is undeniably a promising concept backed by solid blockchain technology. As a result, predicting the cryptocurrency market is just as important as predicting the traditional stock market.

Machine learning (ML) is a type of artificial intelligence that uses past data to predict the future. Prior research has shown that ML-based models have several advantages over other forecasting models, including delivering a prediction that is close to or identical to the actual result and improving the accuracy of the outcome. Neural networks (NN), support vector machines (SVM), and deep learning are examples of machine learning concepts. We discovered the advantages and disadvantages of bitcoin value prediction by combining information from various reference papers and applying it in real-time. Each paper has its own set of methodologies for predicting bitcoin prices. In proportion to how many people can predict and how many cannot, the market is extremely volatile, which presents an opportunity in terms of prediction. In addition, Bitcoin has set a benchmark in cryptocurrency around the world with growing improvements over time. It functions on a decentralized, peer-to-peer, and trustless system in which all transactions are posted to an open ledger called the blockchain. Other financial markets have never seen such transparency.

Although various theories and algorithms for predicting bitcoin prices have been developed, the majority of them have been shown to need to be reconsidered to avoid overfitting and errors caused by large datasets. The LSTM algorithm can be used to forecast bitcoin's future value. The LSTM is very efficient and gives us the most precise results. We can save a large amount of data and predict the most accurate results by using this algorithm.

2. Methodology

2.1 Machine Learning

The Machine Learning forecasting algorithm employs more complex features and predictive methods, but the method's main goal is to improve prediction accuracy while lowering the loss function (sum of squares due to errors in prediction).

2.2 Deep Learning

Deep Learning is a popular method for time series forecasting because it can learn and handle temporal dependence and structures like trends and seasonality, as well as handle arbitrary complex input-output mappings and support multiple inputs and outputs.

2.3 Recurrent Neural Network

A type of Neural Network is a Recurrent Neural Network (RNN). The output of the previous step is used as the input to the current step. The hidden state is the most important feature of RNN. The hidden state keeps track of some sequence information. RNN has a "memory" that stores all information about the calculations. It uses the same parameters for each input because it produces the same output by performing the same task on all inputs or hidden layers. Unlike other neural networks, this reduces the complexity of the parameters.

3. Proposed System

The proposed system is an automated application that uses machine learning and a technical trend indicator to predict a price increase in cryptocurrency for various time series. With weekly price prediction, we also try to answer the question: Does cryptocurrency like Bitcoins have the potential to become a primary method of transaction, replacing the US Dollar and other traditional currencies?

The advanced approach for developing a deep learning model to predict bitcoin coin values includes the following steps:

- The model is trained using an LSTM(Long Short-Term Memory)-based classifier that uses BTC-CAD cost information.
- The use of BTC-CAD cost information and news announcements related to crypto enables us to value the significance of these distinct sources and types of information.

The proposed method for developing a deep learning model to forecast bitcoin coin prices included the following steps:

3.1 GATHERING DATA

The need for a dataset is entirely dependent on the project. The data can come from a variety of places, including files, databases, and even sensors. Kaggle.com provided the dataset of bitcoin (BTC[CAD]) values used in this work to build a deep learning model. There are 9 columns and 1098 rows in the entire dataset. The dataset's CSV file contains prices based on a variety of factors, including open, high, closing market price, market volume, and weighted price.

3.2 DATA PRE-PROCESSING

This is the most important step in deep learning because it aids in the development of a high-accuracy model for analysis. Data collected from the site is converted to a clean data set in this step. The data is then divided into two groups: testing and training. (For instance, data can be divided into 80 percent training data and 20% testing data.)

3.3 DATA SCALING PHASE

The data is scaled here to meet the model's requirements. It reshapes data to improve the model's suitability.

3.4 MODEL-BUILDING PHASE

The best-performing model is built using the pre-processed data. Tensor flow is used as the backend engine, and Keras is used to improve the prediction model's accuracy.

3.5 MODEL LEARNING PHASE

After the training data has been defined, the model is configured to begin the learning phase. The compile method of the Keras sequential model is used to accomplish this. The data is passed to the model for training after the fully configured neural network has been defined. The fit method is used to accomplish this.

3.6 EVALUATION

This is an important component because it aids in the selection of the best model for representing data and the accuracy of the prediction. The model is fed input values, and the output is the predicted value. To calculate accuracy and RMSE values, the output is compared to the testing data.

Time-Series data is a type of sequential data in which the occurrence of events is determined by the passage of time. If a proper output is to be obtained from the data, a network with access to prior knowledge is required to fully comprehend the data. A Recurrent Neural Network is used to accomplish this.

It uses its internal state to process sequential data (memory).

There are three layers in total:

- The input is received by the input layer, which is defined by its weights and biases (in sigmoid function).

- The activation function is applied here, and the output is sustained in the output layer.

When long-term dependencies are present, this type of neural network faces the problem of vanishing gradient. Because the parameters are so large, data training becomes a challenge. Many solutions have been developed to address this issue.

The LSTM and GRU solve the long term dependencies successfully –

Long Short Term Memory (LSTM): The advancement of recurrent neural network architecture used in deep learning models to deal with the problem of vanishing gradient of RNN is known as long short term memory. In terms of module architecture, LSTM differs from RNN. The RNN has only one neural network layer, whereas the LSTM has four layers that interact to produce output.

Gated Recurrent Unit (GRU): The advanced version of the LSTM neural architecture, the gated recurrent unit, also solves problems with long-term dependencies. The LSTM and GRU neural networks produce similar results at times, but their architecture is different. This network is capable of simultaneously managing long-term and short-term dependencies. The LSTM network's three gates are replaced by two gates in GRU, reducing the network's complexity.

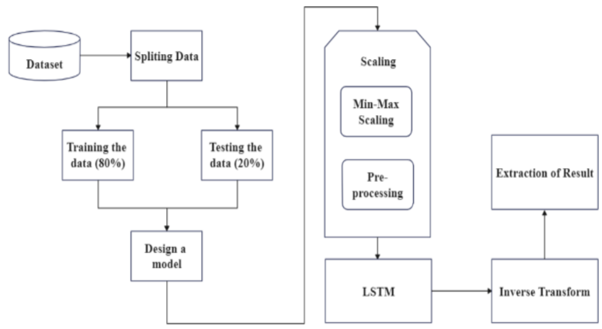
Convolution Neural Network(CNN): A convolution neural network (CNN) is another important deep learning algorithm that has made significant progress in the field of computer vision. This neural network is related to the mathematical term convolution, as the name suggests. In comparison to other deep learning algorithms, data preprocessing is much less. CNN's architecture is similar to that of fully connected networks found in the brain. A layer's single neuron is connected to all neurons in the adjacent layer. The data is overfitted as a result of these fully connected networks. Because this network cannot remember, it only considers the input rather than the hidden state, as an RNN does.

Support Vector Machine(SVM): We developed SVM as a machine learning regressor algorithm to compare our deep learning models. In comparison to another backpropagation algorithm, it has proven to be a good prediction algorithm for stock prices. This algorithm can be used in both classification and regression problems, but it is most commonly used in classification. Each data value in SVM is plotted in n-dimensional space, with each feature representing a coordinate in the space. The two classes are distinguished by classification, which forms the hyper-plane for excellent class differentiation. The thumb rule for identifying the hyperplane is to choose the hyperplane that separates the two classes the best.

4. System Architecture

A quick method for predicting cryptocurrency values:

- Obtaining real-time cryptocurrency information
- Gather information for training and testing units.
- Using deep learning and the LSTM neural network architecture, predict the price of the cryptocurrency.
- Create a visual representation of the prediction results.



(Figure-4.1 - Architecture of the proposed system)

We use Python and Flask to deploy our model to the website. The dataset is prepared for the deep learning model, and all of the changes are passed on to the framework, which employs user interfaces. Authorized licensed use is limited to obtaining user data before making a prediction.

The deployment is carried out in the following manner:

- The file containing the code for the LSTM model for bitcoin price prediction is saved in the same directory as the files below.

- Another file is created, containing Flask APIs that receive data from the user via GUI or API calls.

- Inside the file, a request module will be created, which will be used to call an API and display the returned value.

- Finally, HTML templates and CSS styling are created to develop Flask's GUI and are saved in the same directory as the other files.

4.1 Technologies Used

4.1.1 ANACONDA: Anaconda is the most popular Python distribution platform for data science and machine learning, as well as dealing with large data and its predictions. It includes a variety of environments, including Spyder, Jupyter notebook, Jupyter lab, and Pycharm, all of which can be run and maintained independently. Its cloud repository contains approximately 7500 packages. Instead of using command line commands, the Anaconda Navigator, a desktop GUI that comes with the Anaconda individual edition, can be used.

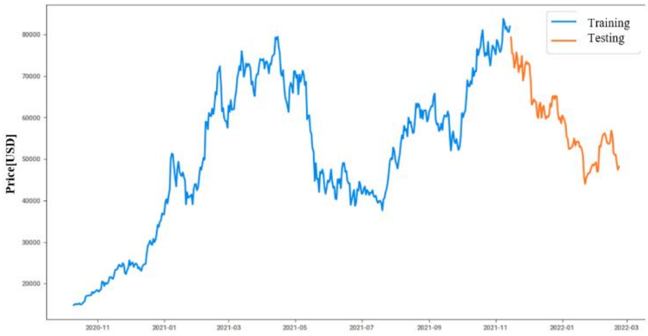
4.1.2 FLASK: Flask is a Python web framework that allows users to create applications such as web pages, blogs, and wikis using its tools and libraries. It's a Unicode-based debugger and development server. In the project, this framework is used to deploy the built model.

4.2 Modules

4.2.1 Train_test_split

- As shown in Figure-4.1, the entire dataset is divided into two sets: a train dataset and a test dataset.
- Items in the train dataset are compromised from the start to the end of the prediction days.
- The test dataset contains all values from a specific index that is between the entire length of the series and the prediction days, i.e. the back dataset.
- Once the process is complete, the Technical Trend Indicator is used to generate a graph (Figure-4.2).

```
def train_test_split(df, test_size=0.2):
    split_row = len(df) -
 int(test_size * len(df))
    train_data = df.iloc[:split_row]
    test_data = df.iloc[split_row:]
    return train_data, test_data
train, test = train_test_split(hist, test_size=0.
2)

def line_plot(line1, line2, label1=None, label
2=None, title='', lw=2):
    fig, ax = plt.subplots(1, figsize=(13, 7))
    ax.plot(line1, label=label1, linewidth=lw)
    ax.plot(line2, label=label2, linewidth=lw)
    ax.set_ylabel('price [CAD]', fontsize=14)
    ax.set_title(title, fontsize=16)
    ax.legend(loc='best', fontsize=16);

line_plot(train[target_col], test[target_col], '
training', 'test', title='')
```



(Figure-4.2-Graph of the trained and tested dataset)

4.2.2 Normalize_min_max

- After the train test split, the developed model is scaled using the cyclic learn min-max scalar, as shown in Figure 4.1.
- Because scaling may cause data leakage from the test to the train set, this is done after the training and testing phases.
- The Min-max scalar converts each data point into a range of zeros to ones.
- After that, the data generator function is used to prepare our data for the LSTM model feed.

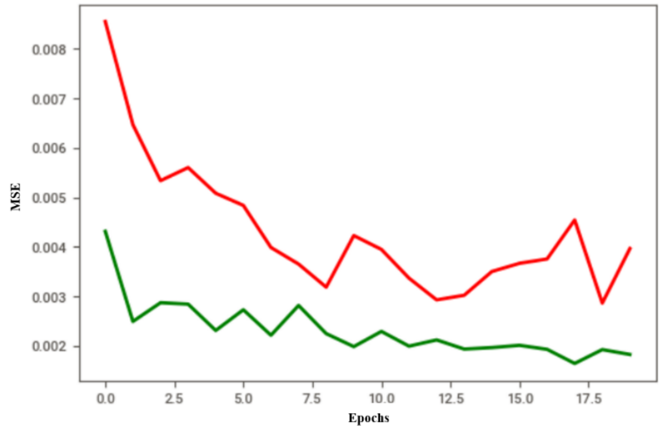
```
def normalise_zero_base(df):
    return df / df.iloc[0] - 1

def normalise_min_max(df):
    return (df - df.min()) / (data.max() -
 df.min())

def extract_window_data(df, window_len=5
, zero_base=True):
    window_data = []
    for idx in range(len(df) - window_len):
        tmp = df[idx: (idx + window_len)].copy(
)
        if zero_base:
            tmp = normalise_zero_base(tmp)
        window_data.append(tmp.values)
    return np.array(window_data)

def prepare_data(df, target_col, window_len
=10, zero_base=True, test_size=0.2):
    train_data, test_data = train_test_split(df,
test_size=test_size)

    X_train = extract_window_data(train_data
, window_len, zero_base)
    X_test = extract_window_data(test_data,
window_len, zero_base)

    y_train = train_data[target_col][window_l
en:].values
```

```
    y_test = test_data[target_col][window_len
:].values

    if zero_base:
        y_train = y_train / train_data[target_col
][:-window_len].values - 1
        y_test = y_test / test_data[target_col][:-
window_len].values - 1

    return train_data, test_data, X_train, X_tes
t, y_train, y_test
```

4.2.3 Build_Lstm_model

- We will face a VANISHING GRADIENT PROBLEM in our model because we are working with a large set of data and multiple RNN layers.
- LSTM is used to solve this problem because it is capable of recalling RNN weights and inputs over a long period.
- We predict validation loss and dataset loss using lstm to find epochs, then mean square error, as shown in Figure-4.3.
- The trained dataset is indicated by the red line, while the tested dataset is indicated by the green line.

```
def build_lstm_model(input_data, output_si
ze, neurons=100, activ_func='linear',
                dropout=0.2, loss='mse', optimiz
er='adam'):
    model = Sequential()
    model.add(LSTM(neurons, input_shape=(
input_data.shape[1], input_data.shape[2])))
    model.add(Dropout(dropout))
    model.add(Dense(units=output_size))
    model.add(Activation(activ_func))
    model.compile(loss=loss, optimizer=opti
mizer)
    return model
np.random.seed(42)
window_len = 5
test_size = 0.2
zero_base = True
lstm_neurons = 100
epochs = 20
batch_size = 32
loss = 'mse'
dropout = 0.2
optimizer = 'adam'

train, test, X_train, X_test, y_train, y_test = p
repare_data(
    hist, target_col, window_len=window_len,
 zero_base=zero_base, test_size=test_size)

model = build_lstm_model(
    X_train, output_size=1, neurons=lstm_neu
rons, dropout=dropout, loss=loss,
    optimizer=optimizer)
history = model.fit(
    X_train, y_train, validation_data=(X_test, y
_test), epochs=epochs, batch_size=batch_siz
e, verbose=1, shuffle=True)

import matplotlib.pyplot as plt
plt.plot(history.history['loss'],'r',linewidth=
2, label='Train loss')
plt.plot(history.history['val_loss'], 'g',linewi
dth=2, label='Validation loss')
plt.title('LSTM')
plt.xlabel('Epochs')
plt.ylabel('MSE')
plt.show()
```



(Figure-4.3 - Generated graph of LSTM model)

4.2.4 Inverse_Transform

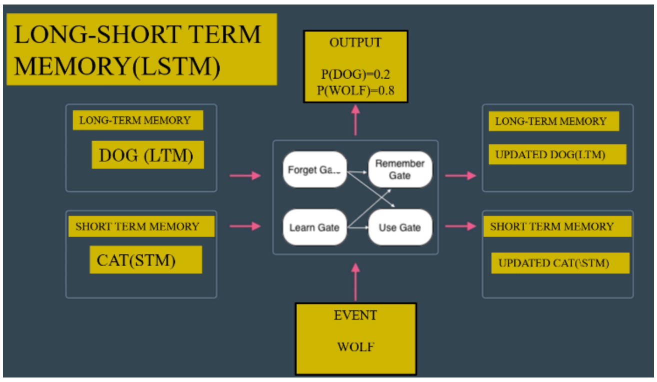
- For prediction, we use Inverse Transform to convert the 0's and 1's values back to normal values.
- It takes any probability distribution and generates a random number.
- The graph shows the actual and predicted values (Figure-4.4).

```
targets = test[target_col][window_len:]
preds = model.predict(X_test).squeeze()
mean_absolute_error(preds, y_test)

from sklearn.metrics import mean_squared
_error
MAE=mean_squared_error(preds, y_test)
MAE

from sklearn.metrics import r2_score
R2=r2_score(y_test, preds)
R2

preds = test[target_col].values[:-
window_len] * (preds + 1)
```

```
preds = pd.Series(index=targets.index, data
=preds)
line_plot(targets, preds, 'actual', 'prediction'
, lw=3)
```

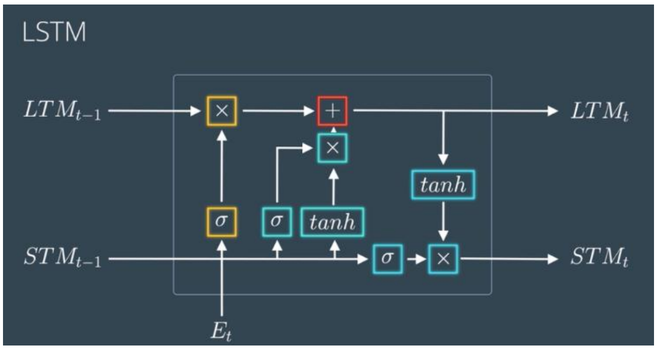
(Figure-4.4 - Graph of actual and predicted value)

5. Algorithm of the overall process



(Figure-5.1 - LSTM Architecture)

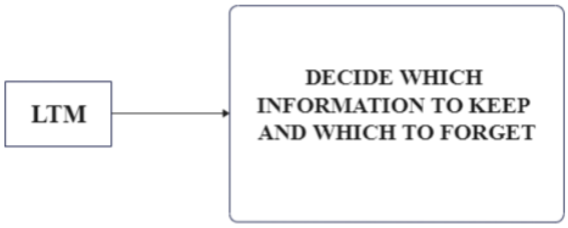
The mathematical architecture of the Long-Short Term Memory(memory) is shown in the following Figure-5.2



(Figure-5.2 – Mathematical Architecture of LSTM)

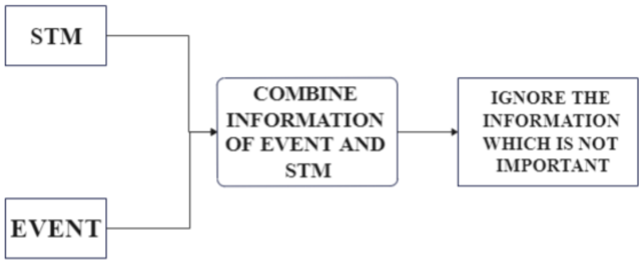
LSTMs deal with both Long Term Memory (LTM) and Short Term Memory (STM), and they use the concept of gates to make calculations simple and effective, as shown in the LSTM architecture diagram (Figure-5.1). A typical LSTM network is made up of various memory blocks known as cells. The cell state and the hidden state are both transferred to the next cell. Memory blocks are in charge of remembering things, and memory manipulation is accomplished through three major mechanisms known as gates.

5.1 Forget Gate: As shown in Figure 5.3, the LTM enters the forget gate and forgets information that is no longer useful. The sigmoid layer is responsible for this.



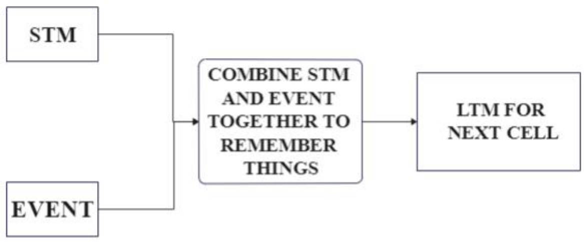
(Figure - 5.3 – Forget Gate)

5.2 Learn Gate: As shown in Figure 5.4, the event (current input) and STM are combined so that the necessary information learned from STM can be applied to the current input.



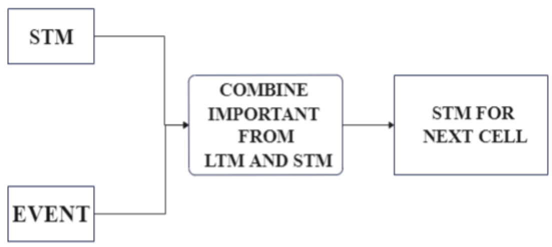
(Figure - 5.4 – Learn Gate)

5.3 Remember Gate: Remember gate combines LTM information that we haven't forgotten with STM and Event to create an updated LTM as shown in Figure 5.5.



(Figure - 5.5 – Remember Gate)

5.4 Use Gate: As shown in Figure 5.6, this gate also uses LTM, STM, and Event to predict the output of the current event, which functions as an updated STM.



(Figure - 5.6 – Use Gate)

The RNN (Recurrent Neural Network with Long Short-Term Memory) is a type of artificial neural network that connects nodes to form a directed graph along a sequence, allowing the network to exhibit dynamic temporal behavior for a time sequence. Long short-term memory networks (LSTM) are a type of RNN that can learn long-term dependencies, making them ideal for predicting time-series data like cryptocurrency price trends.

The main feature of LSTM networks is that each neuron can hold a state and can remove or add information to it using custom structures called gates. A sigmoid neural network layer and a pointwise multiplication operation are used to create these gates. A sigmoid layer produces a value between 0 and 1 that represents the amount of each component that is allowed through.

Three gates regulate and control the state of the neurons in an LSTM neural network.

- The first step in an LSTM process is deciding what information from the cell state to discard. The forget gate makes this decision based on the previous output and current input.
- Based on the previous state and the new input, the next step is to determine the neuron's new state, which is controlled by another gate called the input gate.
- The final step is to filter the updated state and calculate the neuron's final output. The output gate will make this decision based on the current input and the updated state of the cell while keeping a copy for the next input.

LSTM layer: The LSTM layer is the internal one, and all of the gates mentioned earlier are implemented using Keras, with a hard-sigmoid activation by default.

Dropout layer: This comes before the dense layer. A dropout can be added after any hidden layer in Keras, but we do so after the LSTM.

Dense layer: This is a connected layer.

Activation layer: Because we're dealing with a regression problem, the final layer should provide a linear combination of the activations from the previous layer along with weight vectors. As a result, this activation is linear. It could be passed as a parameter to the previous dense layers if desired.

The long short-term memory network, or LSTM, is a recurrent neural network that addresses the problem of disappearing gradients. This is a type of recurrent neural network used in profound learning because it can train very large architectures. As a result, the network can develop long-term trust. The forget and remember gates in an LSTM cell allow the cell to decide whether to block or transmit information based on its strength and importance.

As a result, weak signals that keep the gradient from dissolving can be blocked. The RNN and LSTM network's performance is evaluated to determine the model's effectiveness and efficiency. The input, output, and forget gates of the LSTM unit are used to control the data that flows in and out of the unit. These gates are also used to remember values over arbitrary time intervals of 15 seconds. To handle possible lags in time series, LSTM is commonly used for classifying and making predictions based on time series data.

6. Advantages of the Proposed System

- The system makes use of efficient technologies to make it more robust, resulting in accurate and promising results.
- The model developed with LSTM is more accurate than traditional deep learning models.
- In our case, LSTM (Long Short-Term Memory) is an efficient learner in terms of recognizing long-term dependencies in training data.
- This project uses daily Bitcoin price fluctuations to investigate the model's future predictability with hourly price fluctuations.

7. Performance Analysis

The LSTM is much better at learning long-term dependencies in terms of temporal length. As a result, selecting a long window had a lower impact on the LSTM. The autocorrelation lag was used as a guideline in this process, which was similar to the RNN. On smaller window sizes, the LSTM performed poorly. The most accurate method was LSTM. The performance benefits of parallelizing machine learning algorithms on a GPU are evident in the training of the LSTM model, which improved by 70.7 percent. It may be possible to achieve better results by approaching the task solely from the standpoint of classification.

8. Conclusion

The LSTM is much better at learning long-term dependencies in terms of temporal length. As a result, selecting a long window had a lower impact on the LSTM. The auto-correlation lag was used as a guideline in this process, which was parallel to the RNN. On smaller window sizes, the LSTM performed poorly. The highest accuracy was achieved by LSTM. The performance benefits of parallelizing machine learning algorithms on a GPU are evident in the training of the LSTM model, which improved by 70.7 percent. Looking at the task solely from the perspective of vast classification, it may be possible to improve prediction output. RNN and LSTM deep learning models are effective for Bitcoin prediction, with the LSTM being more capable of recognizing longer-term dependencies. Overall, given the numerous forces influencing the market, predicting a price-related variable is difficult. Add in the fact that prices are heavily influenced by prospects rather than historical data. However, we now have a better understanding of Bitcoin and the LSTM architecture thanks to the use of deep neural networks. Implementing hyperparameter tuning to obtain a more accurate network architecture is currently in progress. Other characteristics can also be considered (although from our experiments with Bitcoin, more features have not always led to better results).

Various deep learning algorithms, such as GRU, LSTM, and CNN, were found to be successful in prediction, and they were compared to the machine learning algorithm SVM. Deep learning models are thought to take a long time to train. Because bitcoin price prediction is based on a large dataset, it was a difficult task. Without real-time deployment, machine learning or deep learning models are useless. API was created specifically for this purpose. This is our current work in progress.

9. Future Work

There is always room for improvement as we work. It is possible to increase the number of neurons. Large column data sets will yield better results. It is always better to include more features or parameters. We can also develop an android app or a website for the same in the future, depending on our needs.

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