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Market Risk Assessment Using Deep Learning Model and Fog Computing Infrastructure

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Abstract

Background: Assessing credit risk is a crucial duty inside financial institutions, ensuring sound lending procedures and reducing the probability of defaults.
Objectives: Traditional methods can face challenges in adapting to changing market conditions and handling large volumes of data. Machine learning (ML) offers an appealing solution by enabling automated and data-driven methods for credit risk assessment.
Methods: This article explores the application of machine learning techniques, including classification algorithms like logistic regression, decision trees, and ensemble methods, in assessing credit risk.
Statistical Analysis: We go into the methodologies tailored for credit risk assessment, encompassing feature selection, model training, and evaluation techniques.
Findings: Moreover, we shall delve into the advantages of machine learning in capturing complex relationships within data, enhancing prediction accuracy, and reducing false positive identifications.
Applications and Improvements: By using machine learning, financial institutions may improve the effectiveness of credit risk assessment, streamline decision-making procedures, and ultimately foster a more resilient lending ecosystem.

Keywords: Machine learning, Financial markets, Risk management, Predictive accuracy, Predictive Modelling, Decision- making.

1. Introduction

Within the domain of finance, the adept handling of market risks is crucial to guarantee the stability and profitability of investments. Market risk, arising from variables including changes in asset values, interest rates, and macroeconomic metrics, presents substantial obstacles to investors and financial entities on a global scale [1]. Conventional risk assessment techniques frequently encounter challenges in comprehensively addressing the intricate and ever-changing characteristics of market fluctuations, resulting in less effective decision-making and heightened susceptibility to negative occurrences [2].
Recently, the emergence of machine learning (ML) has transformed risk management methodologies by providing robust instruments for scrutinizing extensive datasets and deriving important perspectives [3]. Machine learning models, utilizing sophisticated algorithms and

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computational methods, have the capability to improve forecast precision, uncover concealed patterns, and measure risk exposures instantaneously. Through the integration of a variety of data sources, encompassing market indices, economic indicators, and alternative data streams, machine learning-based methodologies offer a thorough structure for evaluating several aspects of market risk, such as volatility, liquidity, and credit risk [4].

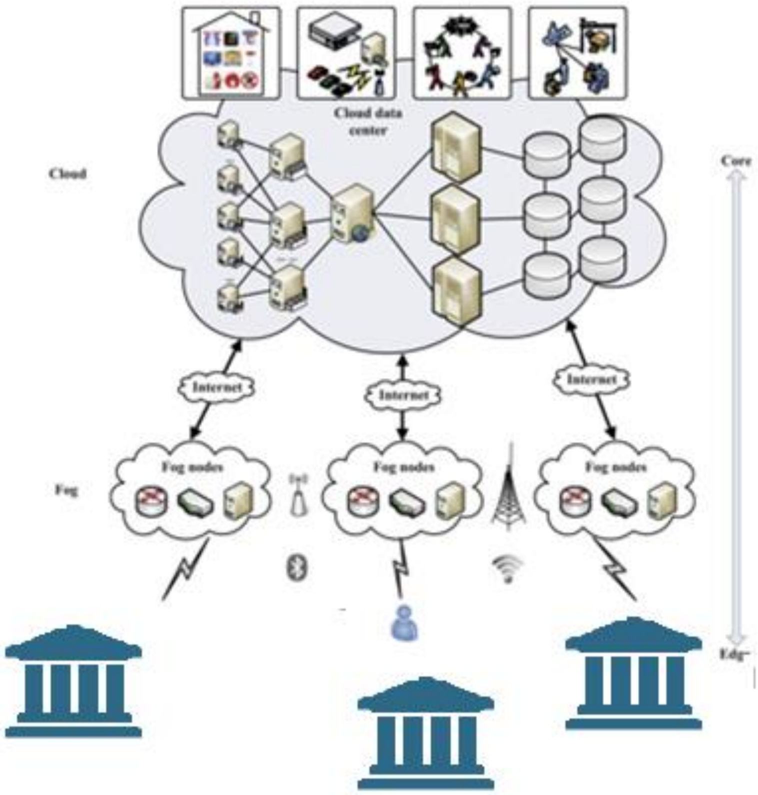

Figure 1. Adopting Fog Computing in Finance Sector

This study delves into the utilization of machine learning models in market risk evaluation, emphasizing its capacity to enhance conventional approaches and enhance risk management procedures. By conducting a thorough analysis of current developments and case studies, we investigate the effectiveness of machine learning-based methods in detecting, quantifying, and reducing market risks. Moreover, we delve into the obstacles and possibilities linked to incorporating machine learning techniques into established risk management frameworks and delineate potential future pathways in this swiftly advancing domain. Through the utilization of machine learning skills, financial institutions may acquire profound insights into market dynamics, improve decision-making procedures, and effectively manoeuvre through unpredictable market situations with heightened assurance and adaptability. Several studies have explored the integration of machine learning (ML) models in market risk assessment, offering valuable insights into the effectiveness of ML techniques in enhancing risk management practices [5].

A large number of financial institutions are making the switch from on-premises to cloud computing [6]. Scalability, dependability, a pay-as-you-go basis, and excellent support are just a few of the numerous benefits. Applications in the medical and financial fields, where communication delays are significant, are not good fits for cloud computing. To address the communicable latency, cloud providers aim to increase the number of regions while still

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ensuring that each area has the right set of functionalities. This led to the development of a novel approach to computing known as Fog Computing, in which data producers are physically nearby computer units [7]. The result is a decrease in the time it takes for a message to receive. Financial institutions are embracing fog computing, as shown in Figure 1.

Market risk identification is a critical aspect of risk management in financial markets. It helps in preserving capital, maintaining financial stability, Optimizing Risk-Return Trade-off, Facilitating Strategic Planning, Protecting Shareholder Value, and Promoting Business Resilience [8]. Through the efficient identification and control of market risks, individuals involved in a particular venture may minimize possible financial setbacks, capitalize on advantageous situations, and successfully attain their desired financial goals within an unpredictable and ever-changing market setting. Hence it is important to detect or predict market risk with highest accuracy. The proposed model uses various strategies to reduce the latency and improve the accuracy. The rest of paper is organized as follows: section 2 discusses various work on market risk detection, assessment and prediction, The proposed model and its working principle is presented in section 3. Section 4 presented results of proposed model and compared with state of art existing machine learning models, section 5 concludes with future research work.

2. Related Work

Multiple research endeavours have delved into the use of machine learning (ML) models in market risk evaluation, providing significant perspectives on the efficacy of ML methodologies in augmenting risk management protocols.

Market risk assessment has been employed within the realms of the financial and banking sectors. The banking sector is embracing novel approaches of Artificial Intelligence. The proposed structure employs machine learning methodologies to address the issue of market risk evaluation. The support vector machine (SVM) approach exhibits advantages, notably the independence between algorithm complexity and its efficacy. An experiment demonstrates that the support vector machine (SVM) technique excels in assessment tasks but with a trade-off in accuracy. The work in [9] undertook an exhaustive examination of machine learning applications in financial risk management, highlighting the significance of machine learning algorithms in forecasting market risks such as volatility and tail events. Their research underscored the dominance of machine learning-based methodologies compared to conventional models in collecting intricate non-linear correlations and enhancing the precision of predictions.

Similarly, authors delved into the exploration of deep learning methodologies, namely recurrent neural networks (RNNs) and long short-term memory (LSTM) networks [10], for the purpose of modelling financial time series data to evaluate market risk. Their study showcased the capacity of deep learning models to grasp temporal relationships and produce resilient risk predictions, surpassing traditional time series techniques. An innovative framework introduced for evaluating market risk by employing ensemble learning methods, including random forests and gradient boosting machines [11]. Their strategy utilised the variety of ensemble models to alleviate model bias and enhance risk prediction accuracy under various market situations.

Furthermore, a deep learning framework [12], such as convolution neural networks (CNNs) and recurrent neural networks (RNNs), for predicting market volatility. Their research demonstrated the capacity of deep learning models to comprehend temporal relationships and derive significant patterns from high-frequency financial data. Moreover, a study conducted by Tsantekidis et al. (2020) delved into the application of natural language processing (NLP)

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methodologies to scrutinize textual information extracted from financial news articles and social media platforms with the aim of conducting sentiment analysis and predicting risks. Their discoveries emphasized the significance of integrating other data sources and sentiment analysis to improve market risk assessment algorithms.
Moreover, research conducted [13][14] delved into the use of reinforcement learning (RL) algorithms in the realm of dynamic portfolio optimization and risk management. Their study emphasized the capacity of RL-based methodologies to dynamically modify investing tactics in accordance with evolving market circumstances and mitigate negative outcomes.
The existing model's accuracy is very less and they have not considered important factors for Market risk assessment. The Machine learning based works have bit higher accuracy but more false positives. So, it is essential to resolve these issues and improve the accuracy of Market risk detection model.

3. Proposed Model

By utilizing the capabilities of deep learning, Long Short-Term Memory (LSTM) networks may be utilized to evaluate market risk. This entails analysing sequential data, such as previous stock prices, in order to forecast future moves in financial markets. For the purpose of analysing time series data, LSTM networks, which are a form of recurrent neural network (RNN), are an excellent choice because of their capacity to identify long-term dependencies. Following subsection describe the deep learning modelling for Market risk assessment.

Data Collection

The historical data is collected from various sources and preprocess these data in next step. Various data collection models presented in literature can be used or any data collection model can be developed. The scope of the article is to modelling market risk assessment model so we are using our existing data collection model called hybrid push pull mechanism [15]

Data Preprocessing

One of the most important steps in the process of preparing financial data for the purpose of training machine learning models such as LSTM is data preparation. It entails a number of actions to guarantee that the data is clean, standardised, and appropriate for the training of the model [15]. The following is an in-depth explanation of the stages involved in the preparation of the data:
Preparing the Data: Eliminate any duplicates: As duplicate entries have the potential to bias the analysis, it is important to check for and eliminate any duplicate data points. Handle values that are missing, which involves replacing missing values with an appropriate estimate such as the mean or the median.
Normalization: Transform the data by normalizing the numerical characteristics to a scale that is comparable. This phase is essential, particularly when employing neural networks such as LSTM, because it facilitates faster convergence during training and prevents characteristics with bigger scales from dominating the learning process of the model.
Features selections: Choose attributes that are pertinent: Pick the characteristics that are most likely to have an effect on the exposure to market risk. Historical prices, trade volumes, technical indicators, economic indicators, and sentiment data are all examples of what may fall under this category.
The Generation of Sequences: LSTM models require input data to be in sequential format, hence it is necessary to convert the data into sequences. To generate input sequences, pick a

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window of historical data points (for example, the previous N days) to use as input features, and then select the next data point (for example, the closing price of the next day) to include as the target variable.

Test, Validation, and Training Split: Once the data has been pre-processed, separate it into three sets: training, validation, and testing. For the purpose of training the LSTM model, the training set is utilized, the validation set is utilized to adjust hyperparameters and monitor model performance while the model is being trained, and the test set is utilized to evaluate the performance of the final model. The following equation are used to collect and preprocess the data

$$\mathrm{CD}_t = \frac{DP(t) - DC(t)}{MAX} X\,100 \tag{1}$$

$$\mathrm{Avg\_stat\_window} = \frac{\sum_{i=1}^{N}(w_i)}{N} \tag{2}$$

$$DUI = \mathrm{CI\ x}\left[1 - \frac{|MAX\_CriticalVal - Curr\_Val|}{MAX}\right].\, UTD \,.\left[1 - \frac{Avg\_stat\_window}{MAX}\right] + \Delta \tag{3}$$

if current MAXCrit< Avg_stat_window

$$\mathrm{DUI} = \mathrm{CI\ \ x}\left[1 - \frac{|MIN\_CriticalVal - Curr\_Val|}{MAX}\right] .UTD \,.\left[1 - \frac{Avg\_stat\_window}{MAX}\right] + \Delta \tag{4}$$

if current MINCrit> Avg_stat_window

$$\mathrm{DUI} = \mathrm{CI\ x}\left[1 - \frac{UTD\, x \left[1 - \frac{Avg\_stat\_window}{MAX}\right] + \Delta}{100}\right] \tag{5}$$

The eq (1) and (2) used to avoid the duplicate data and eq.(3)(4)(5) are used to regulate the data flow based on the critical values.

$$\bar{x} = \frac{\sum_{i=1}^{N} x}{N} \tag{6}$$

$$Median = \left(\frac{n+1}{2}\right)^{th} term \text{ (if n is even)} \tag{7}$$

$$Median = \frac{\left(\frac{n}{2}\right)^{th} term + \left(\frac{n}{2}+1\right)^{th} term}{2} \text{ (If n is odd)} \tag{8}$$

Scaling these data to the trained machine learning / deep learning model is crucial. The scaling can be done via the subsequent equation:

$$x^i_{scale} = \frac{x^i - x^i_{min}}{x^i_{max} - x^i_{min}}, i = 1, \ldots, k, \tag{9}$$

Eq.(6) to eq(9) are used preprocess the data . eq.(6),eq(7) and eq(8) are used to handle the missing values and eq(9) is used normalize the data.

Feature Engineering

Feature engineering is a crucial step in building machine learning models for market risk assessment using LSTM networks. It involves selecting, creating, and transforming features from the raw data that can help the model effectively capture patterns and relationships in the financial time series data [16]. Feature Selection: Choose which features to include in your model. These features can be derived from various sources such as: Historical Prices, Trading Volume, Technical Indicators, including moving averages, Market Indices, Economic Indicators and Sentiment Analysis. The proposed model uses 20+ features presented in result section

The Deep Learning Modelling

LSTM refers to a long short-term memory. This architecture is a subset of recurrent neural networks (RNNs) and is well-suited for processing and predicting sequential data. A major drawback of classic RNNs is their inability to capture long-term dependencies in sequential data; LSTM networks aim to address this issue [17]. Figure 2 shows the LSTM Cell

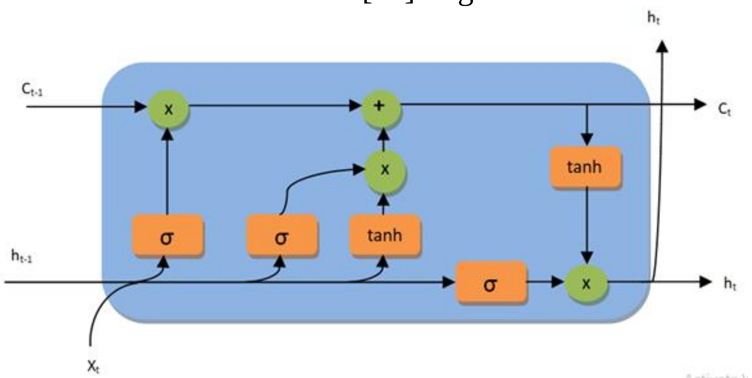

Figure 2. LSTM Model

In order for LSTM networks to function, the data must be presented in a sequential format, with each data point reliant on the ones that came before it. Data that is organized in a sequential fashion includes things; Timestamp followed by selected feature values. A long short-term memory (LSTM) network relies on its memory cell. Long short-term memory (LSTM) networks have memory cells that can hold information over extended periods of time, in contrast to conventional RNNs that only include one recurrent neural unit. To regulate data entry and exit from the memory cell, LSTM networks employ specialized components known as gates. Forget gate decides what old data from the last time step to remove from the current state of the cell. A cell's input gate is responsible for updating its state with any new data acquired at the current time step. Deciding what data from the cell's state to send to the output is the job of the output gate. Through the processing of input data and gate choices, the memory cell updates an internal state known as the cell state. Like a conveyor belt, the cell state selectively updates and forgets information as it moves across time steps [18].

In order to control the flow of information and regulate the state of the memory cell, LSTM networks usually employ activation functions like the sigmoid function (which outputs values between 0 and 1) and the hyperbolic tangent (tanh) function (outputs values between -1 and 1) within each gate and cell state. Training LSTM networks involves the use of gradient-based optimization methods like back propagation through time (BPTT), much like training any other neural network. The network learns to minimize the discrepancy between its predictions and the real targets by adjusting the parameters (weights and biases) of its gates and memory cells

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during training. The following subsection describes design of Market risk assessment model [19].

At time t, the input xt is inputted into the network. The forget gate selectively transmits important information to the cell state based on the relevance of the previous output (ht-1) to the current input (xt). The activation function is applied to the sum of the prior value (ht-1) and the current value (xt) to determine the importance of the previous value. If the output of the activation function is closer to zero, it is deemed insignificant; otherwise, it is seen as significant. Based on the information provided, the forget gate is calculated.

$$f_t = \sigma(Wt_f.[h_{t-1,}X_t] + bs_f \qquad (10)$$

The sign σ symbolises a sigmoid curve, the character "." denotes matrix multiplication, the weights are marked by Wtf, and the bias of the forget gate is denoted by bsf. During the succeeding phase, two processes are executed to determine the new information existing in the cell state. The tanh activation function generates a vector of potential new values when the input gate verifies which states have been modified. Here is an illustration of the created vector.

$$i_t = \sigma(Wt_i.[h_{t-1,}X_t] + bs_i \qquad (7)$$

$$\sim C_t = tanh(Wt_c.[h_{t-1,}X_t] + bs_c \qquad (8)$$

The current cell state Ct is then modified using the outputs from the input gate, forget gate, and tanh layer:

$$C_t = f_t * C_{t-1} + i_t * \sim C_t \qquad (9)$$

Finally, the output gate and a tanh function compute the network's output, as

$$O_t = \sigma(Wt_o .[h_{t-1}, x_t] + bs_o) \qquad (10)$$

$$h_t = O_t * tanh\ (C_t) \qquad (11)$$

(Wto, bso) represents the bias and input weight of the output gate. Dropout regularization is employed to mitigate overfitting problems by selectively removing certain neurons. The purpose of each hidden unit in a neural network is to undergo training using a randomly selected sample of other units. To improve the accuracy of Market risk detection, the hyperparameter tuning is used. The hyperparameters plays a vital role in faster convergence and improve the accuracy. standard values for these hyperparameters instead of random values [17]. The hyperparameters tuning may takes more computational cost but improve the performance.

4. Results and Discussion

This section encompasses the experimental configuration, specifics of the dataset, and evaluation of the performance of the proposed model for detecting suspicious activities. The proposed model is compared to the most advanced suspicious activity detection algorithms. Accuracy and error rates are crucial metrics in the field of market risk identification/ prediction since they serve as key indications for evaluating the effectiveness of classification systems. The performance score is determined using measures, overall accuracy, precision, true positive rate, and true negative rate.

Dataset: To identify risk, we have created our own dataset that contains 20+ features with different types of risk. Table shows the features used in the proposed model

Table 1. Features in the Dataset

Parameter	Description	Typical Value Range
Value at Risk (VaR)	Maximum loss at a given confidence level	Negative value (loss)

Expected Shortfall (ES)	Average loss beyond VaR threshold	Negative value (loss)
Volatility	Degree of variation in asset prices	Non-negative value
Correlation	Degree of association between asset returns	Range between -1 and 1
Beta	Sensitivity of asset returns to market movements	Range including negative values
Liquidity Measures	Indicators of market depth and trading activity	Varies depending on the measure
Stress Testing Scenarios	Extreme but plausible market scenarios	Scenario-dependent
Duration	Sensitivity of bond prices to interest rate changes	Non-negative value
Convexity	Curvature of bond price-yield relationship	Non-negative value
Option Greeks	Sensitivity of option prices to various factors	Range depends on the Greek
Capital Adequacy Ratios	Regulatory capital requirements for market risk	Regulatory thresholds
Market Beta	Sensitivity of portfolio returns to market returns	Range including negative values
Market Volatility	Volatility of the overall market	Non-negative value
Interest Rate Sensitivity	Sensitivity of portfolio value to interest rate changes	Range including negative values
Currency Risk	Exposure to fluctuations in foreign exchange rates	Varies depending on currency pairs
Commodity Price Risk	Exposure to changes in commodity prices	Varies depending on commodity
Sovereign Risk	Exposure to risks associated with sovereign debt	Varies depending on country risk
Geopolitical Risk	Exposure to risks arising from geopolitical events	Scenario-dependent
Counterparty Risk	Risk of default by counterparties	Varies depending on counterparty
Systemic Risk	Risk of widespread financial market disruptions	Scenario-dependent
Risk	The percentage of risk	0-100

Results

In order to assess the effectiveness of the proposed market risk detection model, the root mean square error (RMSE) loss function is computed for both the test dataset and the validation dataset. Figure 3 illustrates the disparity in loss between the training and testing phases across several epochs. The disparity between the test and train loss is minimal, and the loss diminishes as the number of epochs grows. Based on the graph, it can be seen that the suggested anomaly detection model exhibits a high level of accuracy.

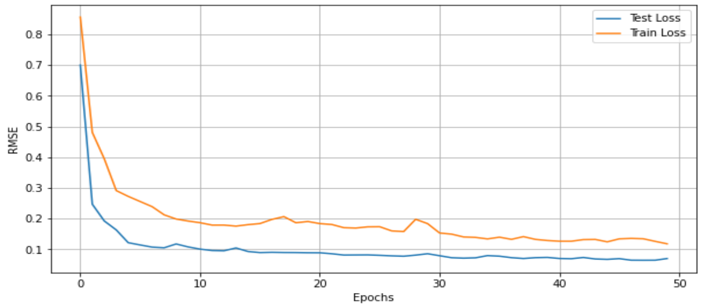

Figure 3. RMSE for Train and Test Dataset

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Table 2 shows the average detection time and accuracy for existing and proposed model. The proposed model improves the accuracy as compared to existing machine learning models. To achieve good accuracy the proposed model used LSTM Deep learning model with hyperparameter optimization. Table 3 shows the confusion metrics of proposed model

Table 2. Comparison of Average Detection Time and Accuracy

Metrics	XG boost	LR Model	KNN Model	SVM	ANN	Proposed
Average Detection time	6	7	8	6	7	5
Accuracy	92	89	87	92	90	94

Table 3. Confusion Metric for Proposed Model

	Predicted Positive	Predicted Negative
Actual Positive	94 (TP)	06 (FN)
Actual Negative	6(FP)	894 (TN)

Table 4 displays the hyperparameter combination that achieved an accuracy of 98.8% when the threshold value was set at 0.65. Based on the experimental findings, it has been discovered that hyperparameter optimization achieved the maximum level of accuracy when compared to other models.

Table 4. Hyperparameter Values for Highest Accuracy

Hyperparameters	Values
Window-size	15
LSTM-Units	30
Dropout-rate	0.2
Regularizer	L2
Regularizer-rate	0.014
Optimizer	RMSprop
Epochs	100
Activation-Function	ReLu
Learning-Rate	0.012

Figure 4 illustrates the comparison of different performance metrics, including CPU use, memory usage, anomaly detection time, and accuracy.

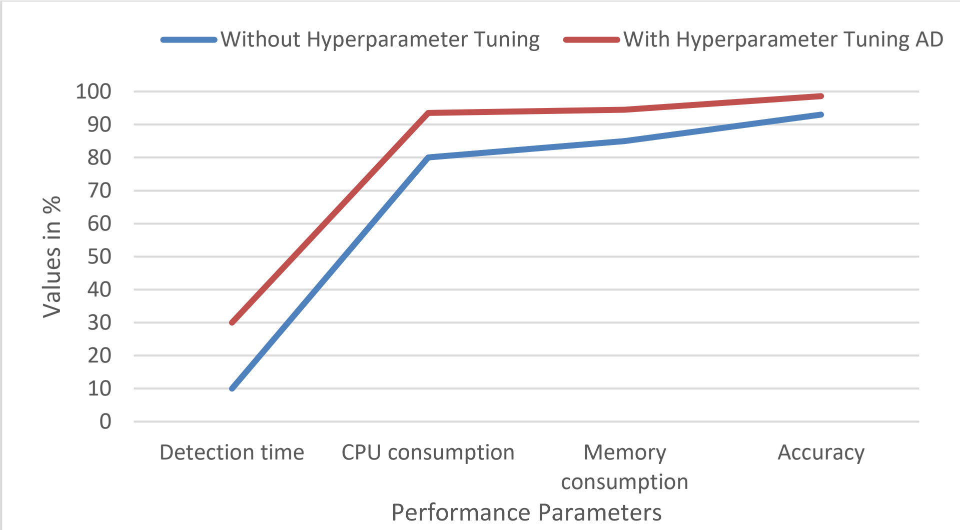

Figure 4. Comparison of Normal AD and Hyperparameter Tuner AD

5. Conclusion

Market risk identification is a critical aspect of risk management in financial markets. It helps for Stakeholders can minimize possible losses, capitalise on opportunities, and accomplish their financial goals in an unpredictable and ever-changing market setting. The existing models not fit dynamic venture of market and have low accuracy and high latency. To resolve these issues, a deep learning model called LSTM used to design a market risk assessment model that has highest accuracy and low latency. The fog computing model is used to reduce the latency and hyperparameter tuning is used to improve the accuracy. A simulation model is designed to evaluate proposed model and existing model. The experiment results show that proposed model has highest accuracy (94%) and low latency as compared to existing model. The future work uses Convolution LSTM model to improve accuracy from 94% to 97%.

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