An Ensemble Learning Approach For Task Failure Prediction In Cloud Data Centers

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Abstract. Due to cloud computing's extensive use and diverse nature, they experience failures in terms of software, service, and platform, which lead to the failure of task execution, resource waste and performance deterioration. Most studies focused on failure prediction resulted in lower prediction accuracies due to limited attributes and a single prediction model. Hence, in this paper, an efficient ensemble model for task failure prediction is put forth.. Initially, the input dataset is collected and pre-processed. In pre-processing, the dataset is cleaned up of all null values. Then, the dimensionality of the pre-processed dataset is reduced by using the PCA algorithm. Thus, the reconstructed dataset is split into training and testing sets to train failure prediction models. The proposed model employs an ensemble learning approach based on different ML and DL algorithms. Then, a comparative study is performed, and the results show that task failure in the cloud system can be effectively predicted using the proposed ensemble method.

1. Introduction

Cloud data centres are becoming increasingly popular due to the wide range of facilities and their adaptability in different domains, such as e-commerce, nuclear science, scientific computing, and healthcare [7].With diverse resource demands and performance objectives, cloud data centers act as a home to a variety of applications. This oversubscription in the resources of cloud data centers overextended the resources, such as CPU and bandwidth, and is shared across many tenants [2]

But the main issues with cloud data centres are resource and task failures, which result in poor customer service quality [11]. Task failure, which can be described as the point at

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which the system is no longer able to meet the task execution demand, is a crucial aspect in a cloud computing environment [1]. Task failure may occur due to various factors, such as software failure, heavy workload execution, hardware failure, service failure, scheduling, and occasionally human errors [8]. The cluster system tries to resume the task if it fails, which affects how the scheduled activities are carried out [10]. Therefore, it is of great significance to identify task failures transpiring in data centers so as to provide satisfactory results to cloud customers and to create appropriate backup plans in case of service interruption[15].

The most recent studies have concentrated on investigating task failures by applying prominent AI techniques, such as Machine Learning (ML) and Deep Learning (DL) [4] to deal with various problems in the prediction of task failure and to ensure high accuracy in the prediction phase [5]. Some grouping techniques were developed by researchers based on task failures, which are unable to provide proper results [14]. The fact that most studies relied on a single classification technique to evaluate their models without comparing them to other classifiers to guarantee that their results were reliable is one of the most important weaknesses of prior research.

1.1 Problem Statement

Various methods were adopted for predicting task failures, but they lead to low prediction accuracy due to the following limitations such as,

- Predictions from a single learning model cannot render accurate predictions due to increased prediction time to find robust decision.
- ML approaches failed to handle large data sequences in cloud data centres due to its training complexity.
- An incomplete database model with the absence of data items leads to an unusual effect of increased classification time.

Hence, to address these shortcomings, an ensembling model was built in this paper with the following contributions,

- To make task failure prediction using an ensemble learning model with good prediction accuracy.
- To introduce deep learning concepts in improving the learning efficiency of sequence data.
- To reduce classification time by removing the presence of null values.

The following sections of the paper are structured as follows: Section 2 examines some related research, Section 3 describes the ensemble model that has been proposed, Section 4 gives the model's performance evaluation, and Section 5 wraps up the paper.

2.Literature Survey

(Li et al., 2023) predicted the workload failures in data centres by analysing the workload traces from the production data centre. The queue-time and runtime predictive models were trained to estimate the workload failures using ML models. Evaluation results showed that the model predicted workload failures with a maximum precision score. The model was inefficient due to the limited number of features.

(Shu et al., 2021) built a powerful task scheduling algorithm to minimise congestion while anticipating task failure rates, study overflow possibility in the task request queue, and investigate response optimisation model. The technique, according to the results, increased the cloud computing system's throughput. In order to handle a huge number of requests, the response optimisation model becomes complex.

(Gao et al., 2022) improved the accuracy of failure prediction by introducing a multi-layer Bidirectional Long Short-Term Memory (Bi-LSTM) failure prediction algorithm. The algorithm identified tasks and job failures in the cloud on the basis of task completion. The experiments showed that the algorithm outperformed other prediction methods with improved accuracy. The Bi-LSTM was slow and time consuming for training.

(Liu et al., 2020) suggested a failure prediction method in regard to the relationships between similar jobs. A job clustering algorithm discovered the high-similarity jobs with various numbers of tasks from which the domain information was utilized by the multi-task learning algorithm. Results showed that higher prediction accuracy was realized than the existing methods. The major limitation of the model was manual feature extraction.

(Padmakumari & Umamakeswari, 2019) executed the workflow in Cloud computing using a failure prediction mechanism. For failure prediction, the model incorporated various ML classifiers. Further, the accuracy was improved by the combined bagging ensemble. The validation of the method indicated that the model predicted the failure with the highest accuracy. The ML algorithms were prone to high error susceptibility.

(Shetty et al., 2019) analysed the workload data on the cloud to characterize the task failures. The failure prediction algorithms were developed based on resource usage data. The XGboost classifier was used to predict task failure using a variety of resampling strategies, and it was shown that the model had enhanced accuracy in predicting the task status. For sparse data, the XGboost technique lacked significant scalability.

(Jassas & Mahmoud, 2019) developed a failure prediction model to detect failed tasks in cloud applications. The model was developed based on different ML algorithms and selecting the best accurate model. Moreover, the model performance was evaluated and ensured that the prediction model provided the highest accuracy of predicted values. However, the model causes some inaccuracies due to the manual training of ML models.

3. Proposed Task Failure Prediction System

This section presents the proposed ensemble learning model for task failure prediction, which takes the training data as input and generates task failure as output. Figure 1 displays the block diagram of the suggested methodology.

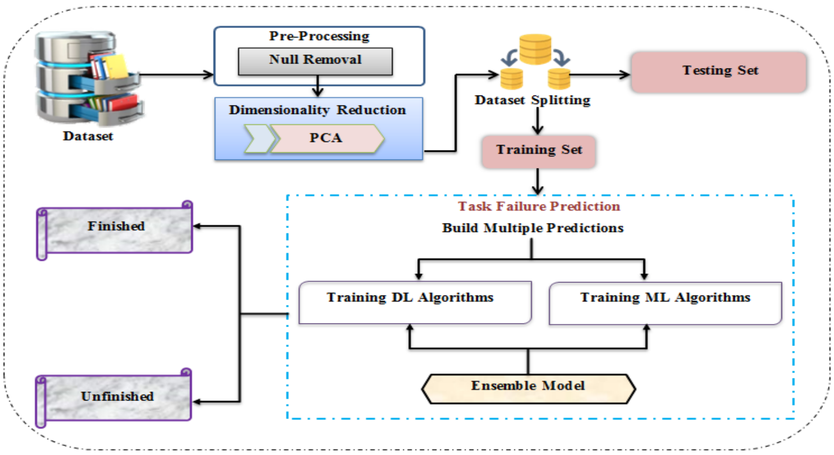


Fig. 1. Flow Diagram of the proposed methodology

3.1 Input Data

In this work, the Google cluster trace dataset is used to obtain data related to tasks. The dataset contains 26 columns with task resource usage measures and various attributes. The input data is expressed as,

$$\chi_{inp(n)} = \left\{ \chi_{inp(1)}, \chi_{inp(2)}, \chi_{inp(3)}, \ldots, \chi_{inp(N)} \right\} \tag{1}$$

Where, $\chi_{inp(n)}$ contains n number of input data.

3.2 Preprocessing

Here, the input data is preprocessed to remove all the null values that affect the performance and accuracy of learning algorithms. Hence, the preprocessed dataset is expressed as,

$$\chi_{nr(n)} = \delta_{neg}\left(\chi_{inp(n)}\right) \tag{2}$$

Where, δ_{neg} denotes the function used to remove all the null values, and $\chi_{nr(n)}$ is the output data after removing all the null values.

3.3 Dimensionality Reduction

After preprocessing, the dimensionality reduction using Principle Component Analysis (PCA) is carried out. PCA helps to remove redundant features such that the learning algorithms perform better and the computation time is decreased.. PCA algorithm returns the most significant data called principle components by computing the Eigenvectors and respective Eigenvalues. The steps are as follows,

Firstly, the preprocessed dataset $\left(\chi_{nr(n)}\right)$ is standardized and the covariance matrix (β) of input is,

$$\chi_{st(n)} = \frac{\chi_{nr(n)} - \mu_{\chi_{nr(n)}}}{\nabla_{\chi_{nr(n)}}} \tag{3}$$

$$\beta = \frac{1}{N}\sum_{n=1}^{N} \chi_{st(n)} * \left(\chi_{st(n)}\right)^T \tag{4}$$

Where, $\chi_{st(n)}$ is the standardized output, $\mu_{\chi_{nr(n)}}$, $\nabla_{\chi_{nr(n)}}$ denotes the mean and standard deviation, and β is the correlation matrix. Next, the Eigen vectors (η) and Eigen values (ϑ) of the covariance matrix are calculated as,

$$\eta\beta = \vartheta.\eta \tag{5}$$

In the end, the dimensionality reduced features are attained by choosing the top eigenvector of the co-variance matrix. Then, the new dataset with reduced attributes is expressed as,

$$\chi_{dr(n)} = \left\{\chi_{dr(1)}, \chi_{dr(2)}, \chi_{dr(3)}, \dots, \chi_{dr(N)}\right\} \tag{6}$$

Thus, the dimensionality reduced data set $\chi_{dr(n)}$ includes 7 columns of parameters, such as CPU resource request, scheduling class, memory resource request, CPU average usage, memory average usage, assigned memory, machine id, page cache memory, and failed(0 or 1) from the original dataset.

3.4 Dataset Splitting

As the learning method has two parts, a training, and a testing phase, the dataset is divided into training and testing in this section. Therefore, using split data, one portion is used to train the model and the other to test the data. The split data is shown as,

$$\chi_{splt} = \left\{\chi_{dr(n)} \mid \chi_{tra(n)}, \chi_{tes(n)}\right\} \tag{7}$$

Where, χ_{splt} denotes the spitted dataset containing training data $\left(\chi_{tra(n)}\right)$ and testing data $\left(\chi_{tes(n)}\right)$.

3.5 Task Failure Prediction

The training data from the splitted dataset $\left(\chi_{tra(n)}\right) \in \chi_{splt}$ is used to build the ensemble learning-based prediction model. By training various DL and ML classifiers,the prediction process is derived as follows,

3.5.1 DL Classifiers

CNN **:** Convolution Neural Network (CNN) has superior performance in learning input data with three main layers. CNN receives input data in the form of matrix. The convolution layer applies filters to input with an activation function that results in the number of feature maps for which dimensionality reduction is carried out using the pooling layer. Finally, the features extracted from the subsequent layers are combined as a feature vector to perform classification in the fully connected layer. The softmax activation function $\left(\psi_{sfm}\right)$ to classify the feature maps is expressed as,

$$\psi_{sfm}\left(G_{inp}\right)=\frac{Exp\left(G_{inp}\right)}{\sum_{n=1}^{N}\left(G_{inp(n)}\right)} \qquad (8)$$

Where, G_{inp} is the input vector after convolution and pooling operations, and N is the number of classes in CNN.

***RNN*:** The same operation is carried out by the recurrent neural network (RNN) for each data input, and the output depends on the results of the preceding computation.. The input state in RNN captures the input data while the output state predicts the result of the model. The hidden states perform all its computations amid the input and hidden states. Then, the output of the network is computed as,

$$\phi_{out(t)} = \varsigma(\theta_{hid,out}\phi_{hid(t)} + \Phi_{(out)}) \qquad (9)$$

Where, $\theta_{hid,out}$ denotes the weight parameters, $\phi_{hid(t)}$ is the output of the recurrent layer, $\Phi_{(out)}$ is the bias of the output layer, and $\phi_{out(t)}$ gives the output of the network at a time step t.

***LSTM*:** Long Short Term Memory (LSTM) is a type of RNN designed to learn long-term dependencies by introducing a memory cell. The memory cell is controlled by three gates, such as forget gate (fg), input gate (ig), and output gate (og) in a manner of deciding information, which should be removed from, add to, and output from the memory cell. The output of each gate is obtained as,

$$fg_{(t)} = \varsigma_{sig}\left(\theta_{fg}\left(hid_{(t-1)}, \chi_{tra(t)}\right) + \Phi_{fg}\right) \qquad (10)$$

$$ig_{(t)} = \varsigma_{sig}\left(\theta_{ig}\left(hid_{(t-1)}, \chi_{tra(t)}\right) + \Phi_{ig}\right) \qquad (11)$$

$$og_{(t)} = \varsigma_{sig}\left(\theta_{og}\left(hid_{(t-1)}, \chi_{tra(t)}\right) + \Phi_{og}\right) \qquad (12)$$

$$CS_{(t)} = og_{(t)} \cdot \varsigma_{\tanh}\left(\chi_{tra(t)}\right) \qquad (13)$$

Where, ς_{sig} is the sigmoid activation function, $\varsigma_{\tanh}$ is the tanh activation function, $\theta_{fg,ig,og}$ denotes the weight matrices of each gate, $\Phi_{fg,ig,og}$ is the bias vector parameters, $hid_{(t-1)}$ is the output from the previous hidden state, and CS is the new cell state.

***Bi-LSTM*:** Two LSTMs make up the bi-directional LSTM (Bi-LSTM), which processes input sequences in both forward and backward directions. Information is processed by the forward LSTM going from left to right. $\left(\overrightarrow{hid}_{(t)}\right)$ whereas the reverse form of input $\left(\overleftarrow{hid}_{(t)}\right)$ is processed by the backward LSTM. Finally, the concatenation of forward and backward states summarizes the output of Bi-LSTM as,

$$hid_{(t)} = \left\{ \overrightarrow{hid}_{(t)} = LSTM\left(\overrightarrow{hid}_{(t-1)}, \chi_{tra(t)} \right), \overleftarrow{hid}_{(t)} = LSTM\left(\overleftarrow{hid}_{(t+1)}, \chi_{tra(t)} \right) \right\} \tag{14}$$

Where, $hid_{(t)}$ is the output of Bi-LSTM network.

***CNN-LSTM*:** The hybridization of CNN and LSTM results in CNN-LSTM. The, CNN is used to construct a feature vector which is then integrated into the LSTM for failure prediction. The fully connected layers make the last layer of CNN-LSTM predict the output as,

$$L_{i,l} = \sum_{i} \theta_{i,l-1} \left(\varsigma_{sig} \left(hid_{(i,l-1)} \right) + \Phi_{i,l-1} \right) \tag{15}$$

Where, $L_{i,l}$ is the output of a fully connected layer, and $\theta_{i,l-1}$ is the weight of the i^{th} node in the l^{th} layer.

3.5.2 ML Classifiers

Random Forest: Random Forest (RF) is an ensemble method that selects the subset of data points from the input data and constructs a decision tree for each sample, which formulates some set of rules to make predictions. The final output is determined based on majority voting for classification. The output is obtained as,

$$O\left(\chi_{tra(n)}\right) = \frac{1}{N} \sum_{n=1}^{N} E_n \left(\chi_{tra(n)}\right) \tag{16}$$

Where, $O\left(\chi_{tra(n)}\right)$ denotes the output of the classifier, N is the number of trees, and E_n is the output of the ensemble of trees.

***Decision Tree*:** A decision Tree (DT) is a supervised learning technique that uses the input data to learn the decision rules in order to predict the target's class. The method begins at the root, where the input population is separated into subpopulations based on different characteristics. It then continues through the branches and concludes with the choice made by the leaves, which is the decision node created by slicing the root nodes. The result is established as,

$$DN\left(\chi_{tra(n)}\right) = \tau\left(h\left(\chi_{tra(n)}\right) \neq L\right) \tag{17}$$

Where, DN denotes the true misclassification rate of decision rule h to make the decision, τ is the probability, and L represents the class label of the input vector.
Hence, the ensemble approach aggregates the single learner's output to construct a voting classifier. The prediction is made by combining multiple classifiers called based learners trained on the input dataset and averaging all the predictions as follows,

$$Y = \frac{1}{M} \sum_{m=1}^{M} BL_{(m)} \left(\chi_{inp}\right) \tag{18}$$

Where, BL denotes the M number of base learners, and Y denotes the output of the voting classifier.

Algorithm 1: Ensemble Learning-based Task Failure Prediction

```
Input: input dataset $\chi_{inp(n)}$
Output: Predicted outcomes
```

```
Begin
        Initialize dataset, learning models, number of iterations $m_{\max}$
        Explore Dataset $\chi_{inp(n)}$
        Remove null values $\chi_{nr(n)}$        //preprocessing
        Reconstruct the dataset $\chi_{dr(n)}$
        Split dataset $\chi_{splt}$              //training and testing
        For $(m=1)$ to $m=m_{\max}$
          Make multiple predictions
                Train DL algorithms
                Train ML algorithms
          Combine predictions        // ensemble learning
                $Y = \frac{1}{M}\sum_{m=1}^{M} BL_{(m)}(\chi_{inp})$
      End for
      Return predicted outcomes
End
```

4. RESULTS AND DISCUSSION

In order to evaluate the efficiency of the proposed model, numerous experiments conducted in the working platform of PYTHON are presented in this section.

4.1 Dataset description

The proposed method utilized the Google cluster trace dataset for the experimental evaluation. The dataset describes every task submission, resource usage data, and scheduling decision for the tasks that ran in those clusters. Using these features, the prediction performance of the proposed model is leveraged.

4.2 Performance Analysis of the proposed framework

The trained models were validated using the test set in this subsection, and the models' performance was assessed using evaluation metrics including accuracy and F1-Score.

Table 1: Performance Measurement of Individual Classifiers

Algorithm	Accuracy (%)	F1 Score (%)
CNN	97.93	97.9
CNN-LSTM	95.23	95.15
LSTM	81.68	76.44
BI-LSTM	84.24	81.46
RNN	88.93	88.42
RF	99.83	99.83
DT	99.64	99.64

Table 1 analyses the accuracy and F1-score attained by individual classifiers. From the results, it can be said that RF shows improved performance in contrast to other individual algorithms with 99.83% of accuracy and F1-score. Hence, the DT model is the best prediction model among all the ensemble learning models.

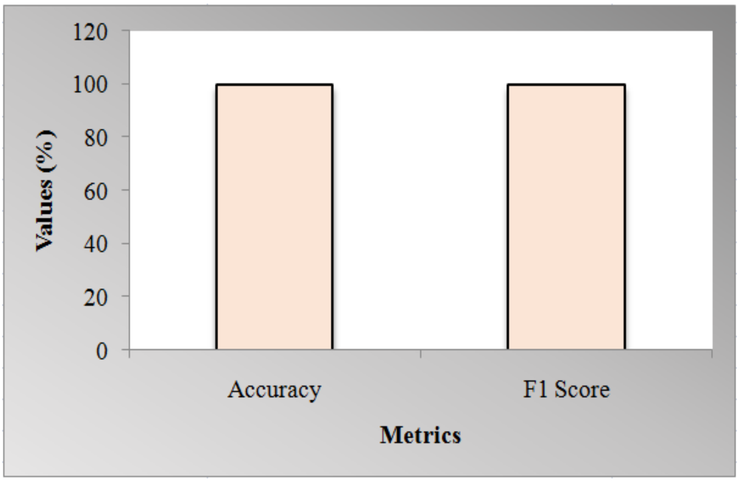
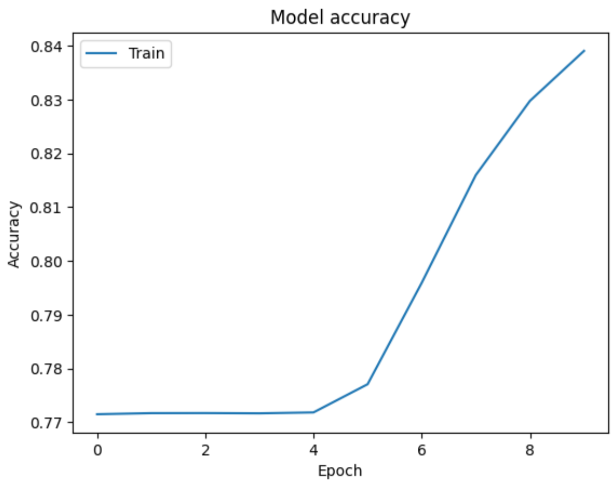
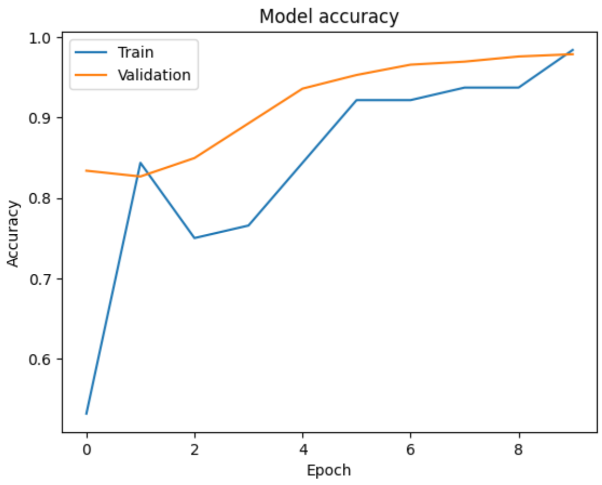


Fig. 2. Performance Analysis under the Combination of all Classifiers using Voting

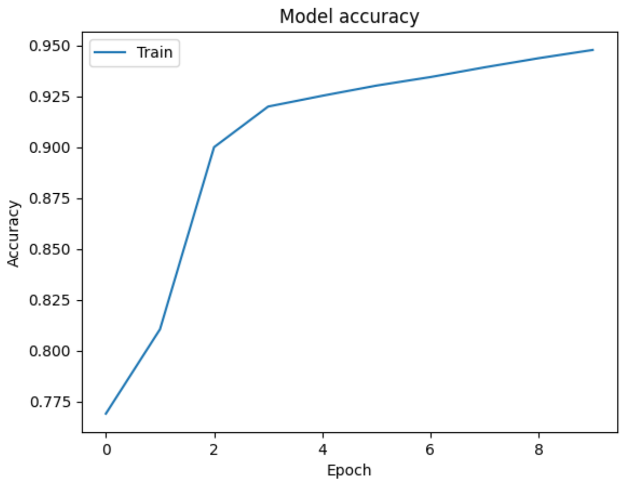
Figure 2 analyses the accuracy and F1-score of the voting classifier. When combining all the classifiers using the voting classifier, the highest prediction accuracy and the F1-score values are obtained. Hence, it clearly demonstrates that the ensemble scheme had a fast influence on the task failure prediction process over the cloud system.


Model accuracy
Train
Accuracy
Epoch
0.84
0.83
0.82
0.81
0.80
0.79
0.78
0.77
0
2
4
6
8

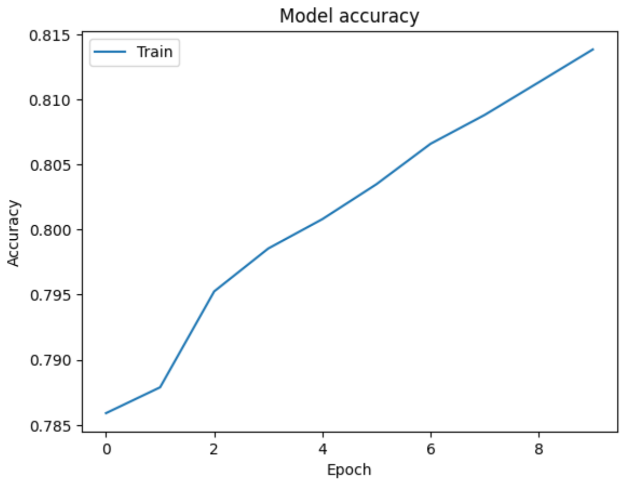
(a)


Model accuracy
Train
Validation
Accuracy
Epoch
1.0
0.9
0.8
0.7
0.6
0
2
4
6
8

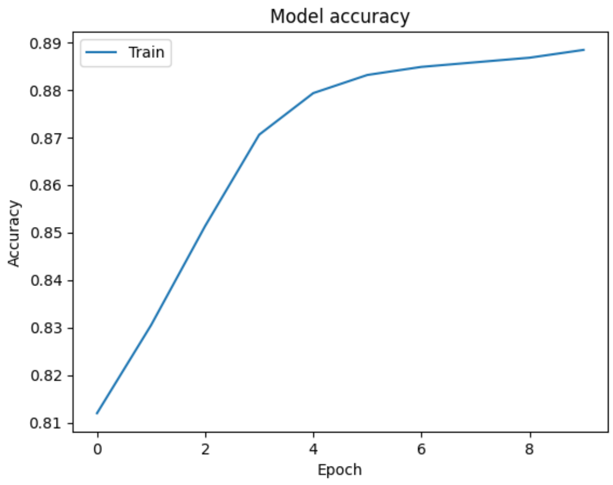
(b)


Model accuracy
Train
Accuracy
Epoch
0.950
0.925
0.900
0.875
0.850
0.825
0.800
0.775
0
2
4
6
8

(c)



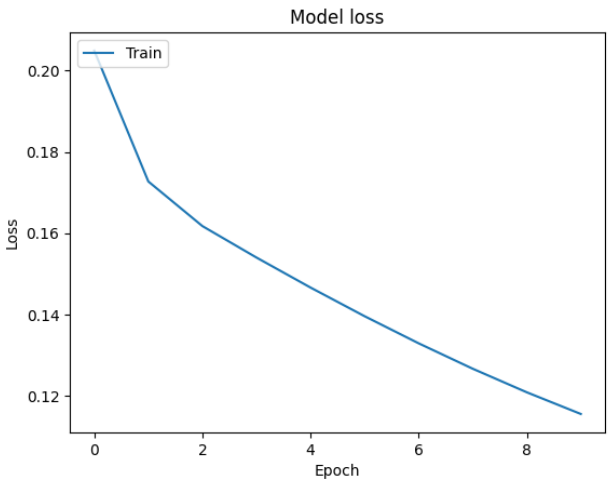
(d)



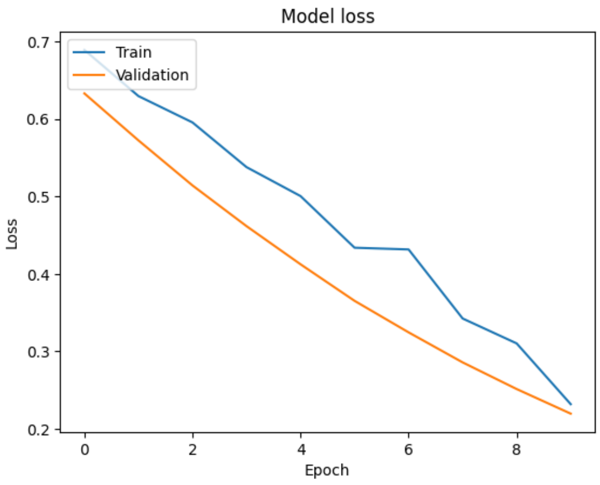
(e)

Fig. 3. Accuracy of DL algorithms (a) Bi-LSTM, (b) CNN, (c), CNN-LSTM, (d) LSTM, and (e) RNN

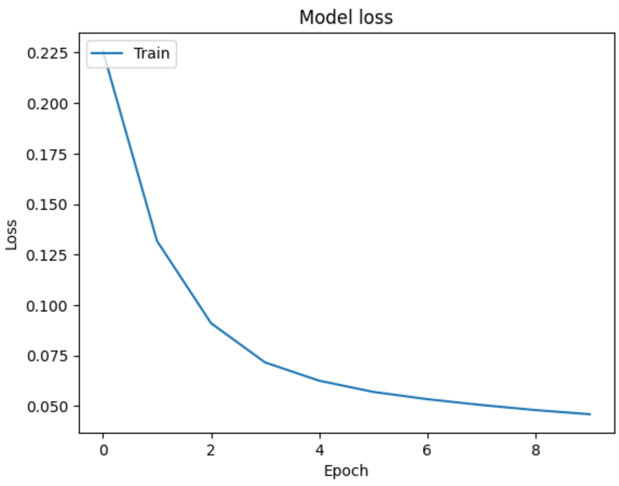
Figure 3 analyses the training accuracy of the DL algorithm with respect to the number of epochs. In comparison, the CNN algorithm attained an accuracy of 0.9793, which is higher compared to other DL methods. Hence, the analysis concludes that efficient preprocessing and dimensionality reduction processes improved the accuracy of the CNN model in task failure prediction.


Model loss
Train
Loss
Epoch
0.20
0.18
0.16
0.14
0.12
0
2
4
6
8

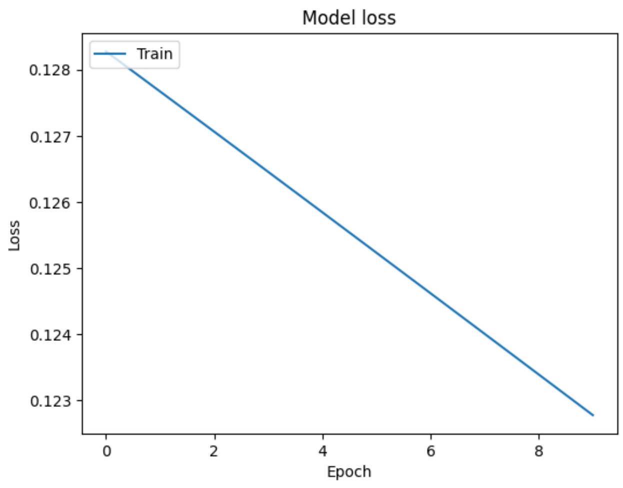
(a)


Model loss
Train
Validation
Loss
Epoch
0.7
0.6
0.5
0.4
0.3
0.2
0
2
4
6
8

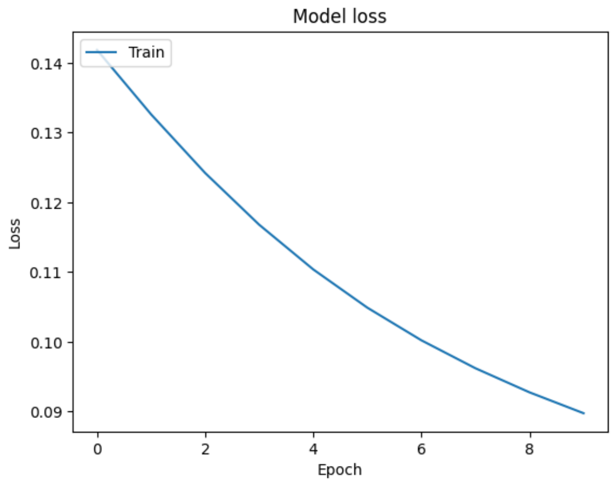
(b)


Model loss
Train
Loss
Epoch
0.225
0.200
0.175
0.150
0.125
0.100
0.075
0.050
0
2
4
6
8

(c)



(d)



(e)

Figure 4: Loss of DL algorithms (a) Bi-LSTM, (b) CNN, (c), CNN-LSTM, (d) LSTM, and (e) RNN

Figure 4 compares the training loss attained by various DL algorithms. While comparing, the training loss of CNN is much lesser than the other DL algorithms. The analysis states that the CNN algorithm has more efficiency over the training data by incorporating a dimensionality reduction process.

Table 2: Comparative Analysis

Methods	**Accuracy (%)**
Proposed Ensemble-RF	99.83
(Gao et al., 2022)	93
(Liu et al., 2020)	96.55
(Padmakumari & Umamakeswari, 2019)	94.4

Table 4 represents the accuracy analysis of the proposed best performance model RF and the recent related works. Even though (Gao et al., 2022) and (Liu et al., 2020) used machine learning algorithms, they attained less efficiency due to the usage single prediction model and lacking of dimensionality reduction. This shows that ensemble learning based prediction improved the efficiency of the proposed model in classifying the failed tasks.

5. CONCLUSION

This paper developed an ensemble-learning-based task failure prediction model for cloud data centers. The model explored the resource utilization information in the cloud system using the latest data from the Google cluster trace dataset. The proposed model consists of five phases. The data were first pre-processed, and dimensionality was reduced using the PCA technique. Thereafter, ensemble learning models were built for task failure prediction. Then, the performance of the six ensemble learning models was compared to demonstrate the superiority of the ML and DL algorithms' performance. It was observed that the CNN, CNN-LSTM, and DT algorithms also attained improved performance. From the analysis, the RF algorithm with the prediction accuracy of 99.9% is found as the best performing model among the ensemble learning models. In the future, the performance of the proposed model is improved by developing a solution for failure recovery that mitigates the failure problems with suitable scheduling decisions.

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