EFFICIENT INTRUSION DETECTION SYSTEM USING HYBRID ENSEMBLE MODEL FOR CLOUD COMPUTING

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INTRODUCTION

- An intrusion detection system (IDS) is a monitoring tool that keeps track of suspicious activity and sends out warnings when it finds something suspicious.
- To address this issue, machine learning algorithms are increasingly being used in IDSs to improve their accuracy and reduce false positives.
- The proposed **hybrid IDS** uses a combination of supervised algorithms such as decision tree, LSTM for intrusion detection.
- The IDS is evaluated using the **CICIDS2017 dataset** and the results indicate that the proposed IDS is able to detect intrusions with a high degree of accuracy.

OVERALL OBJECTIVE

- The main objective of an intrusion detection system (IDS) using ensemble algorithms in a cloud environment is to detect and prevent cybersecurity threats.
- An IDS with ensemble algorithms **continuously monitors the network traffic in the cloud environment** in real-time to detect any anomalies or suspicious activities.
- The ensemble algorithms analyze large volumes of data to identify patterns and detect potential threats before they can cause harm to the system or network.
- Once a threat is detected, the **IDS can respond quickly to prevent the threat** from spreading or causing further damage.

- Cloud-based IDS using ensemble algorithms can easily scale to **handle large volumes of data** and multiple locations, providing a comprehensive view of the network.
- By detecting and preventing cybersecurity threats, the IDS helps to minimize the risk of data breaches, financial loss, and reputational damage to the organization.
- Overall, the objective of an IDS using ensemble algorithms in a cloud environment is to provide a proactive approach to cybersecurity, identifying and preventing threats before they cause significant harm to the system or network.

LITERATURE SURVEY

Ref. no	Paper Title, Authors,Year, Journal name,Vol, Issue & pp	Methodology/ Technique/ Algorithm Used	Advantages	Issues / Gaps / Limitations	Ideas for adoption
1.	W. Wang, X. Du, D. Shan, R. Qin and N. Wang, "Cloud Intrusion Detection Method Based on Stacked Contractive Auto-Encoder and Support Vector Machine," in IEEE Transactions on Cloud Computing, vol. 10, no. 3, pp. 1634-1646, 1 July-Sept. 2022.	Support vector Machine	SACE (feature extraction)	Cannot efficiently detect unknown attacks	Feature Extraction (SCAE)

Ref. no	Paper Title, Authors,Year, Journal name,Vol, Issue & pp	Methodology/ Technique/ Algorithm Used	Advantages	Issues / Gaps / Limitations	Ideas for adoption
2.	A. M. Vartouni, S. S. Kashi and M. Teshnehlab, "An anomaly detection method to detect web attacks using Stacked Auto-Encoder," 2018 6th Iranian Joint Congress on Fuzzy and Intelligent Systems (CFIS), 2018, pp. 131-134.	Isolation forest	Detection of unknown attacks	High false alarm rate	Auto Encoder model
3.	A. Javadpour, S. Kazemi Abharian and G. Wang, "Feature Selection and Intrusion Detection in Cloud Environment Based on Machine Learning Algorithms," 2017 IEEE International Symposium on Parallel and Distributed Processing with Applications and 2017 IEEE International Conference on Ubiquitous Computing and Communications (ISPA/IUCC), Guangzhou, China, 2017, pp. 1417-1421F	Neural Network, Fuzzy Logic	Suitable for Qualitative features	Low Flexibility	Decision Tree Model

Ref. no	Paper Title, Authors,Year, Journal name,Vol, Issue & pp	Methodology/ Technique/ Algorithm Used	Advantages	Issues / Gaps / Limitations	Ideas for adoption
4.	G. Kene and D. P. Theng, "A review on intrusion detection techniques for cloud computing and security challenges," 2015 2nd International Conference on Electronics and Communication Systems (ICECS), Coimbatore, India, 2015, pp. 227-232	Hybrid based detection	Accurate detection of known attacks	Can’t detect unknown attacks	Different types of Attack generation
5.	M. Ficco, L. Tasquier and R. Aversa, "Intrusion Detection in Cloud Computing," 2013 Eighth International Conference on P2P, Parallel, Grid, Cloud and Internet Computing, Compiegne, France, 2013, pp. 276-283	Artificial Neural Network	Central correlation system to send alerts	Less Accuracy	IDS cloud Architecture

Ref. no	Paper Title, Authors,Year, Journal name,Vol, Issue & pp	Methodology/ Technique/ Algorithm Used	Advantages	Issues / Gaps / Limitations	Ideas for adoption
6.	U. Oktay and O. K. Sahingoz, "Proxy Network Intrusion Detection System for cloud computing," 2013 The International Conference on Technological Advances in Electrical, Electronics and Computer Engineering (TAEECE), Konya, Turkey, 2013, pp. 98-104	Deep learning algorithms	Better at hardware usage	Time taking	Anomaly based IDS
7.	A. Kannan, G. Q. Maguire Jr., A. Sharma and P. Schoo, "Genetic Algorithm Based Feature Selection Algorithm for Effective Intrusion Detection in Cloud Networks," 2012 IEEE 12th International Conference on Data Mining Workshops, 2012, pp. 416-423.	Genetic Feature Selection	Low false alarm rate	Features are removed without any extractions.	Genetic Algorithm model

Ref. no	Paper Title, Authors,Year, Journal name,Vol, Issue & pp	Methodology/ Technique/ Algorithm Used	Advantages	Issues / Gaps / Limitations	Ideas for adoption
8.	H. A. Kholidy and F. Baiardi, "CIDS: A Framework for Intrusion Detection in Cloud Systems," 2012 Ninth International Conference on Information Technology - New Generations, Las Vegas, NV, USA, 2012, pp. 379-385	P2P Network Architecture	Flexibility and Scalability	Not sufficient for detecting large scale attacks	Storage of new attack in database
9.	F. I. Shiri, B. Shanmugam and N. B. Idris, "A parallel technique for improving the performance of signature-based network intrusion detection system," 2011 IEEE 3rd International Conference on Communication Software and Networks, 2011, pp. 692-696.	Parallel Processing	Reduce Process Time	Cannot detect unknown attacks	Signature based Intrusion Detection System

Ref. no	Paper Title, Authors,Year, Journal name,Vol, Issue & pp	Methodology/ Technique/ Algorithm Used	Advantages	Issues / Gaps / Limitations	Ideas for adoption
10.	C. -C. Lo, C. -C. Huang and J. Ku, "A Cooperative Intrusion Detection System Framework for Cloud Computing Networks," 2010 39th International Conference on Parallel Processing Workshops, San Diego, CA, USA, 2010, pp. 280-284	Majority Vote Method	Better accuracy	Less number of attacks detected	Threshold check and Alert System

SUMMARY OF ISSUES:

- As the number of cloud services and users increases, the **amount of data to be analyzed also increases**, making it difficult for traditional intrusion detection systems to handle.

- The data is not created and the utilised datasets are out of date.

- Not detecting the unknown attacks and also having less accuracy

- The accuracy of the system in detecting and classifying attacks is low. **False positives** (i.e., classifying benign traffic as malicious) and **false negatives** (i.e., failing to detect actual attacks) can result in wasted resources and missed opportunities to prevent attacks.

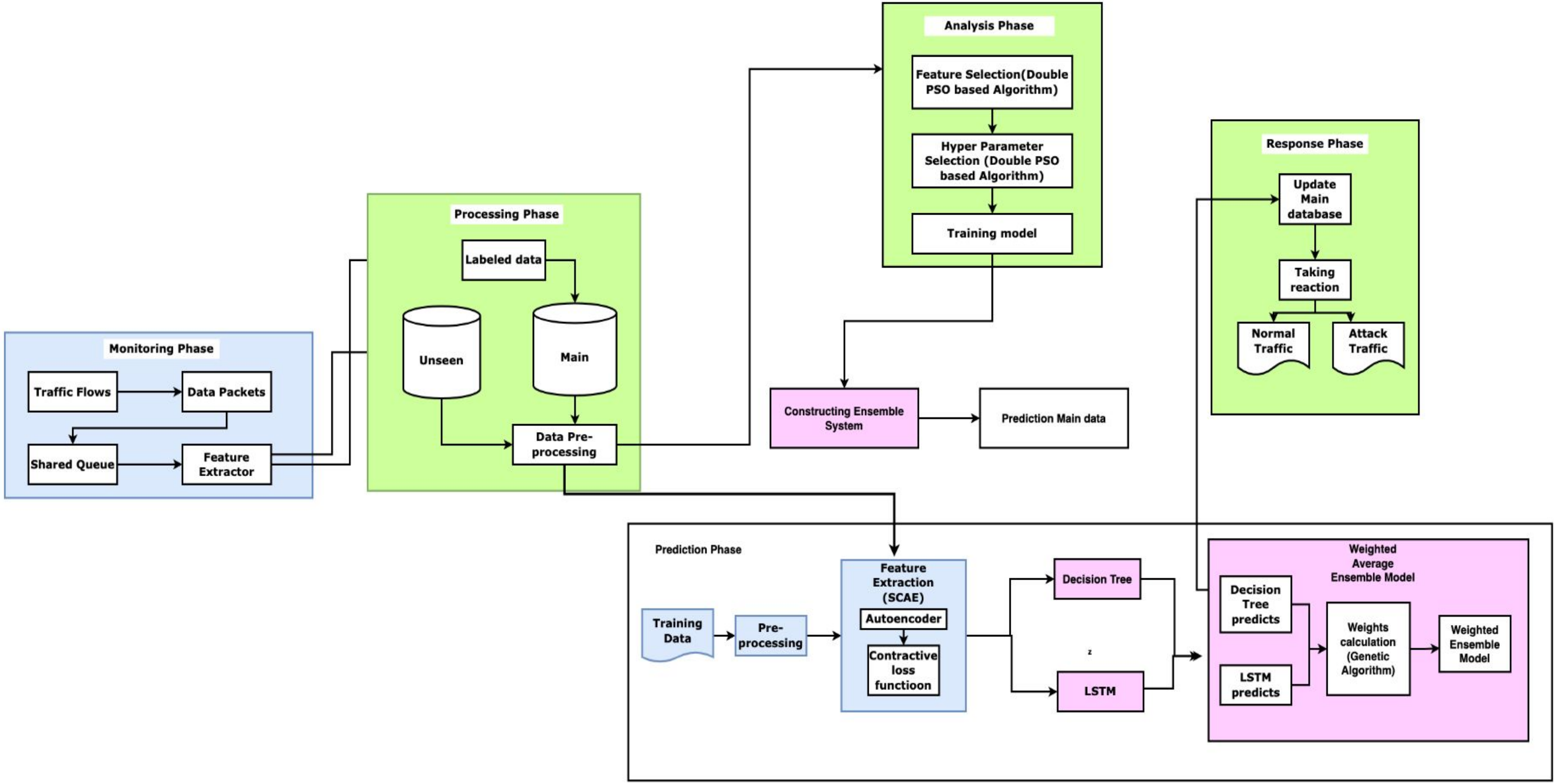
Proposed System

- Used **Weighted average ensemble model** by combining decision tree and LSTM model by generating weights using geneticalgorithm

- Signature based detection by storing new attacks

- Feature selection and hyper parameter tuning using **double particle swarm optimization algorithm**

Overall Architecture



EXPERIMENTAL SETUP

- Azure Virtual Machines
- CIC Flowmeter
- Google Colaboratory
- Numpy
- Tensorflow
- Scipy
- Geneticalgorithm
- Seaborn
- keras

DETAILS OF MODULE DESIGN

List of Modules:

1. Monitoring Phase
2. Processing Phase
3. Analysis Phase
4. Prediction Phase
5. Response Phase

MONITORING PHASE:

- The monitoring module's initial job is to capture all inbound and outbound data packets transiting the cloud network.
- The monitoring module employs sensors to sensitive network traffic to help in this operation.
- The monitoring module **may collect data packets** from various application, transport, and network protocols such as TCP, UDP, ICMP, IP, HTTP, SMTP, and so on.
- The traffic flows are instantly stored in the shared queue.
- The shared queue serves as an intermediary station between packet capture and feature extraction, storing gathered data packets until the feature extractor processes them consecutively

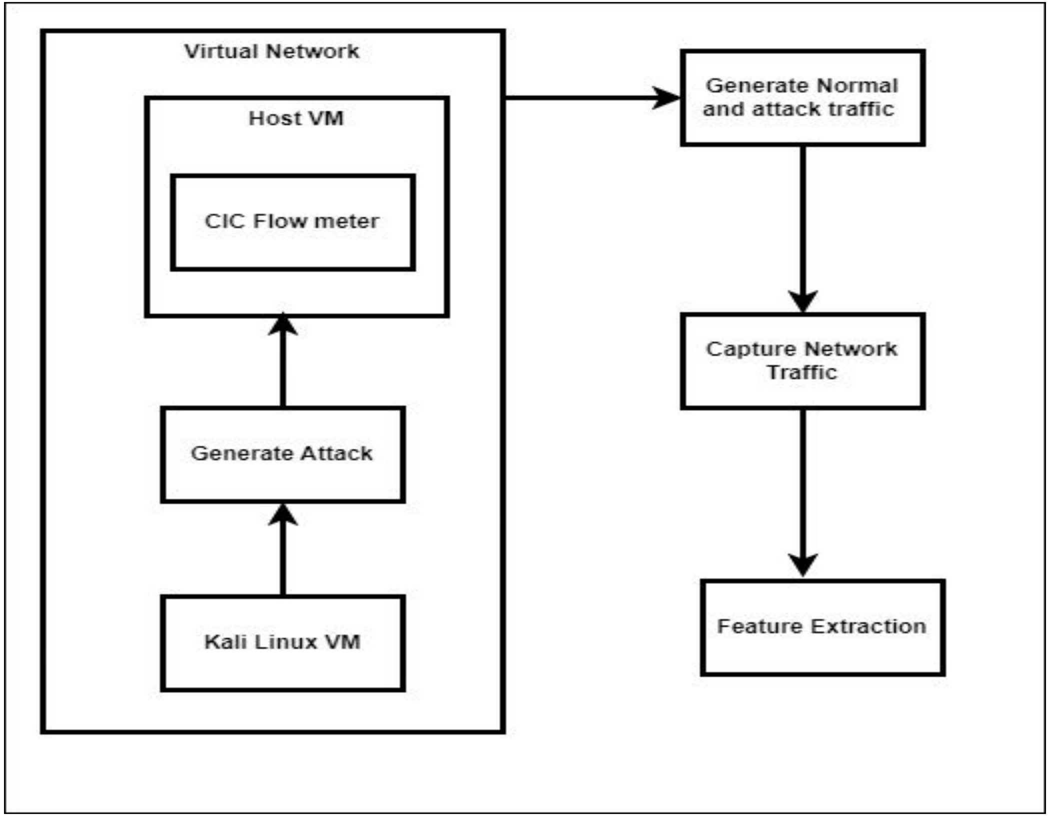


Fig 5.1 MONITORING PHASE

Steps:

1. *Private Cloud is set with multiple Virtual Machine.*
2. *One Virtual Machine, say Kali Linux is used to generate different attack on the host machine.*
3. *CIC Flow meter is used in Host VM to capture the network traffic and export the data as CSV.*
4. *Feature Extraction is to be performed in the exported data.*

PROCESSING PHASE:

- Prior to the forecast procedure, the processing module completes all necessary missions.
- It initially gets data records from the feature extractor and attempts to classify them (as "Normal" or "Attack").
- This is possible by utilizing a **signature-based detection** process, which uses a set of pre-defined criteria (signatures) to match the examined data record against known attack patterns.
- If there is a match, the data record will be categorized as a "Attack". It will be called "Normal" otherwise.
- After that, processing module puts the labeled data record in a database we termed it as "main database".

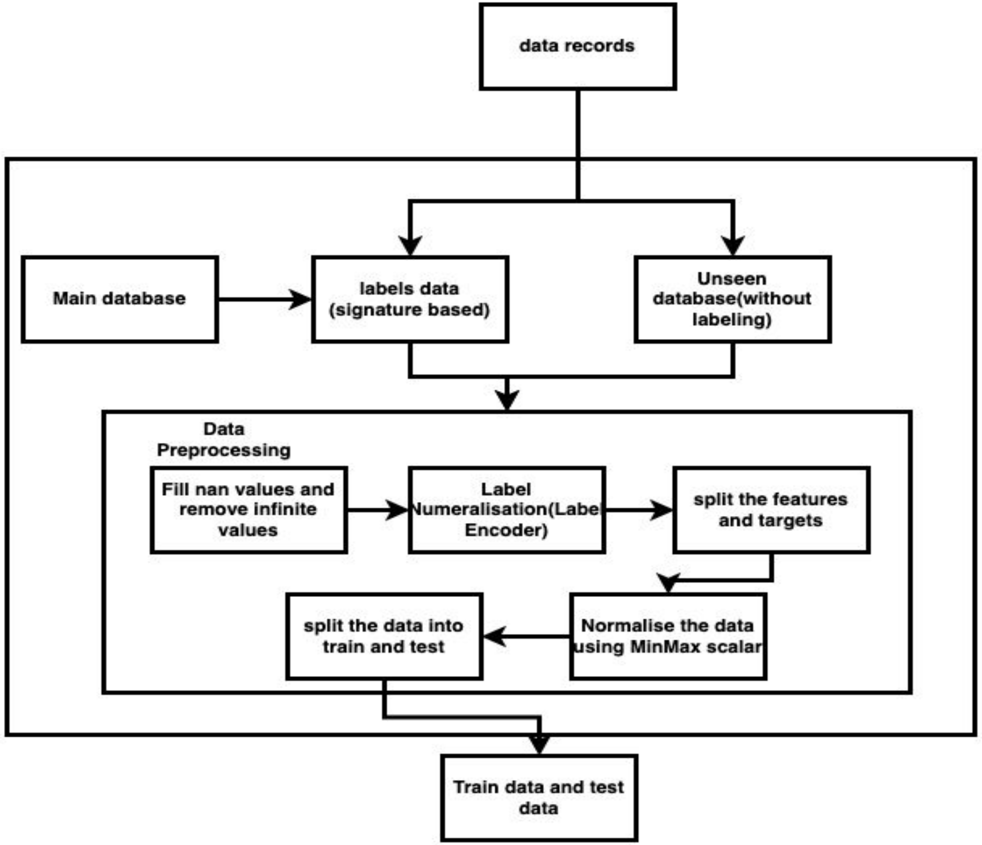


Fig 5.2 PROCESSING PHASE

Algorithm:

1. Remove Nan values and infinite values
2. Using label encoder fit the labels and transform it into numbers
3. Split the features and targets
4. Use normalizer as Min Max scaler

$$xi = (xi - min) / (max - min).$$

5. Split the data into train and test.

PREDICTION PHASE:

- The prediction module, which collects the data from the processing module and also merges the data with the dataset (CICIDS2017), prepares a combined dataset.
- These data will go through the feature extraction algorithm and produce an output dataset, which will be used as the main dataset to train the model.
- The created model performs two sequential tasks, which is the core of the proposed CIDS. The first step is to build the **weighted average ensemble system** utilizing the previously trained decision tree and LSTM models, where the weights for that ensemble model will be generated by the fitness function of the genetic algorithm.
- The prediction module's second purpose is to successively choose a data record from the preprocessed, unseen database.
- Following that, the selected data record is tested using the ensemble system, and the weighted ensemble engine's final judgment is sent to the response module.

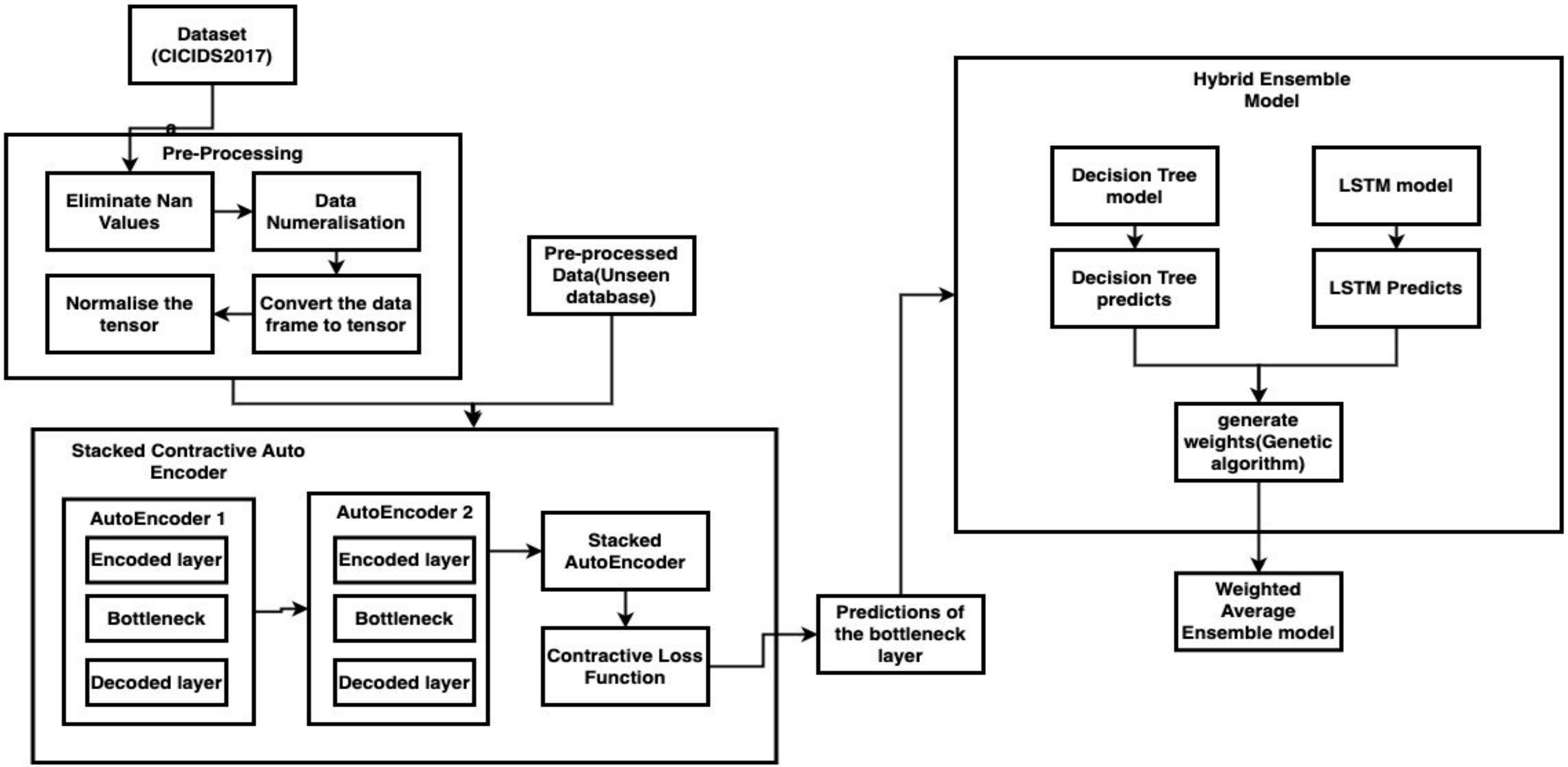


Fig 5.3 PREDICTION PHASE

- First of all, convert the dataset from unbalanced to balanced label encoding, and then normalization is needed. The mini-max transformation is used for normalization,
    - **xi = (xi - min) / (max - min).**

Algorithm-SCAE:

1. *Define hyper parameters like learning rate, coefficient of contractive penalty term (beta)*
2. *Define layers of the autoencoder and stack them on each other*
3. *Define a contractive loss function where,*
    a. *Calculate jacobian matrix and compute each partial derivative and form a matrix*

$$z_{ij} = \delta f_i / \delta x_j$$

b. Calculate Forbenius norm where it is the root of sum of squares of each element in jacobian matrix.

$$y = \sqrt{\sum_{i=0}^{n}\sum_{j=0}^{n} x_{ij}}$$

c. Calculate the contractive penalty

reduce_mean(forbenius_norm)

d. Return loss output as

$$\beta * contractivepenalty$$

4. Compile the model with loss as mean squared error as primary loss and contractive loss as the secondary loss

5. Get the predictions by testing the test data and train data with the model.

Algorithm - Weighted Average Ensemble method:

1. *Create Genetic algorithm with 100 iterations to find weights in order to get good accuracy*

   a. *Define weight bounds*

$$bounds = [(0,1),(0,1)]$$

   b. *Define fitness function*

$$Weight_{predicts} = weight[0] * dt_{predicts} + weight[1] * lstm_{predicts}$$

   c. *Find accuracy for weight_pred*

Accuracy = (TP + TN) / (TP + FP + TN + FN)

   d. *Repeat b and c until 100 iterations.*

2. *By considering weights from step 1, find the accuracy with the test labels and weight preds.*

ANALYSIS PHASE

- The analysis module handles the deep learning models' pre-training and training stages.
- The analysis module runs the **double PSO-based** method for feature and hyper parameter selection during the pre-training phase.
- After data preparation, the analysis module obtains a copy of the main database.
- The upper level of the double PSO-based method is then executed on the main database to determine the best feature subset.
- The main database is then reduced using only the best characteristics.
- Then, using the decreased master database, it conducts the bottom level of the double PSO-based method to generate the ideal hyper parameter vector.

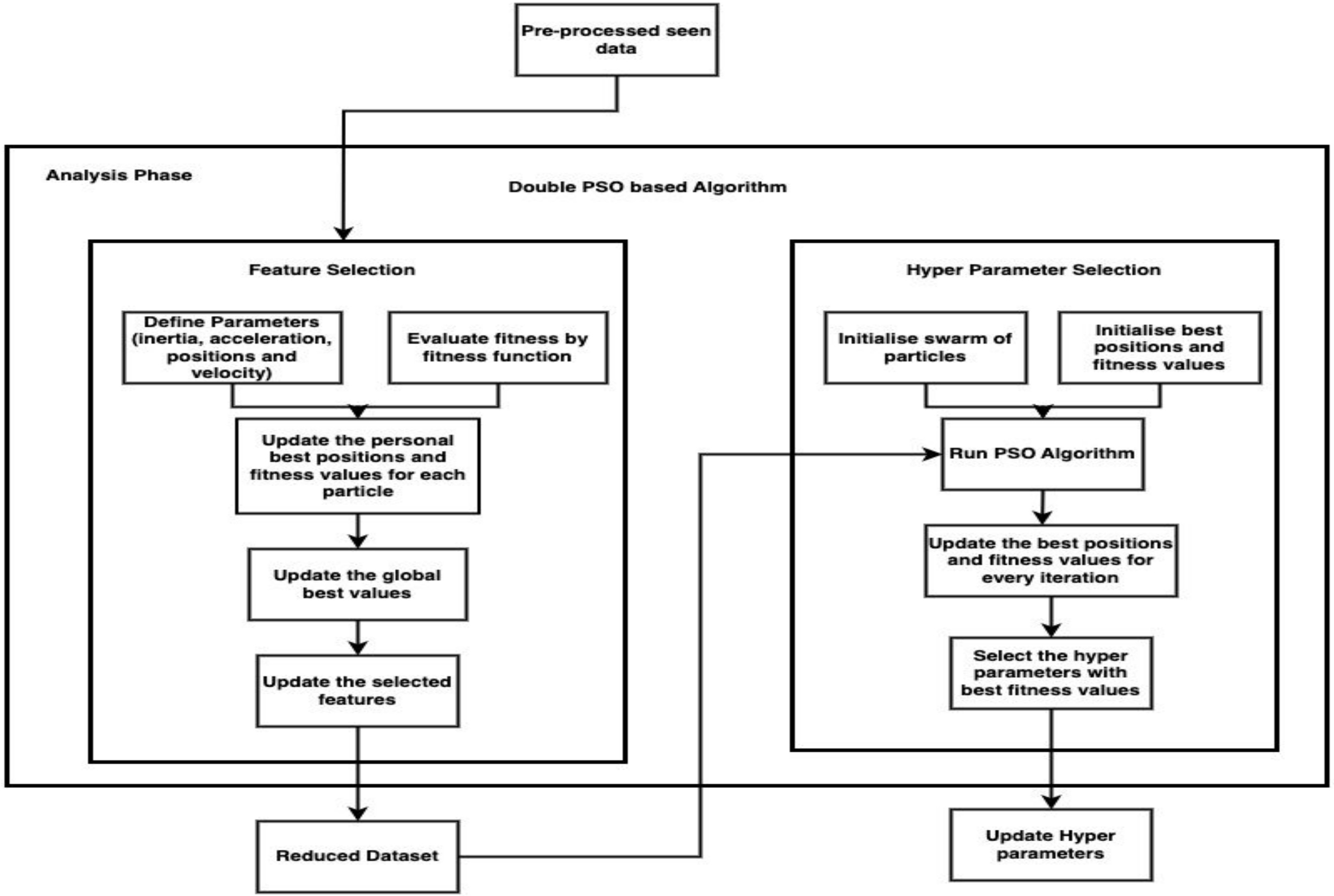


Fig 5.4 ANALYSIS PHASE

Algorithm - Particle Swarm Optimization Upper Level:

1. *Initialize PSO parameters*
2. *Evaluate the fitness of each particle based on the corresponding feature subset*
3. *Update personnel best positions and fitness values for each iteration*
4. *Update global best positions and fitness values for the swarm.*
5. *Update the velocities and positions of the particle.*

$$V_i = w * v_i + c1 * rand() * (pbest_{xi} - x_i) + c2 * rand() * (gbest_x - x_i)$$

$$x_i = x_i + v_i$$

6. *Repeat 2 to 5 until maximum iterations reached*
7. *Select the feature subset corresponding to the global best position.*

Algorithm - Particle Swarm Optimization Lower Level:

1. *Define parameters for PSO*
2. *Initialize swarm particles with randomly using search space*
3. *Evaluate Fitness of each particle*
4. *Update personnel best positions and fitness values for each iteration*
5. *Update global best positions and fitness values for the swarm*
6. *Update Velocity and position of each particle*
   a. *Calculate Inertia weight*

$$w_i = w_{start} - (w_{end} - w_{start}) * (iter / max\_iter)$$

b. Compute Cognitive coefficient

$$v_i = w_i * v_i + c1 * rand() * (pbest_i - x_i)$$

c. Calculate social coefficient

$$v_i = w_i * v_i + c2 * rand() * (gbest - x_i)$$

d. Calculate Cognitive component and Social component

*Cognitive_component = cognitive_coeff * (part [‘personel_best_position’] - part [‘position’]*

*Social_component = social_coeff * (part [‘personel_best_position’] - part [‘position’]*

e. Update the velocity and position of each particle

*Part[‘velocity’] = Part[‘velocity’] * inertia_weight + Cognitive_component + Social_component* *f. Update position of the particle by adding its velocity to its current position.*

7. Repeat 3 to 6 until maximum iterations are done.

8. Select the hyper parameters with the best fitness as the optimal hyper parameter subset.

RESPONSE PHASE:

- The response module receives both the final model and the tested data record, and then labels the tested data record with the final model.
- The **master database is then updated** by storing the new labeled data record at the end of the master database.
- The second function is in charge of reacting to the final decision of "Normal" or "Attack". In the instance of "Normal," the response module instructs the prediction module to go to the next data record in the unseen database in order to forecast its label.
- If, on the other hand, the final choice obtained is "Attack," the response module issues an alert that the cloud network is being subjected to potentially harmful activities.

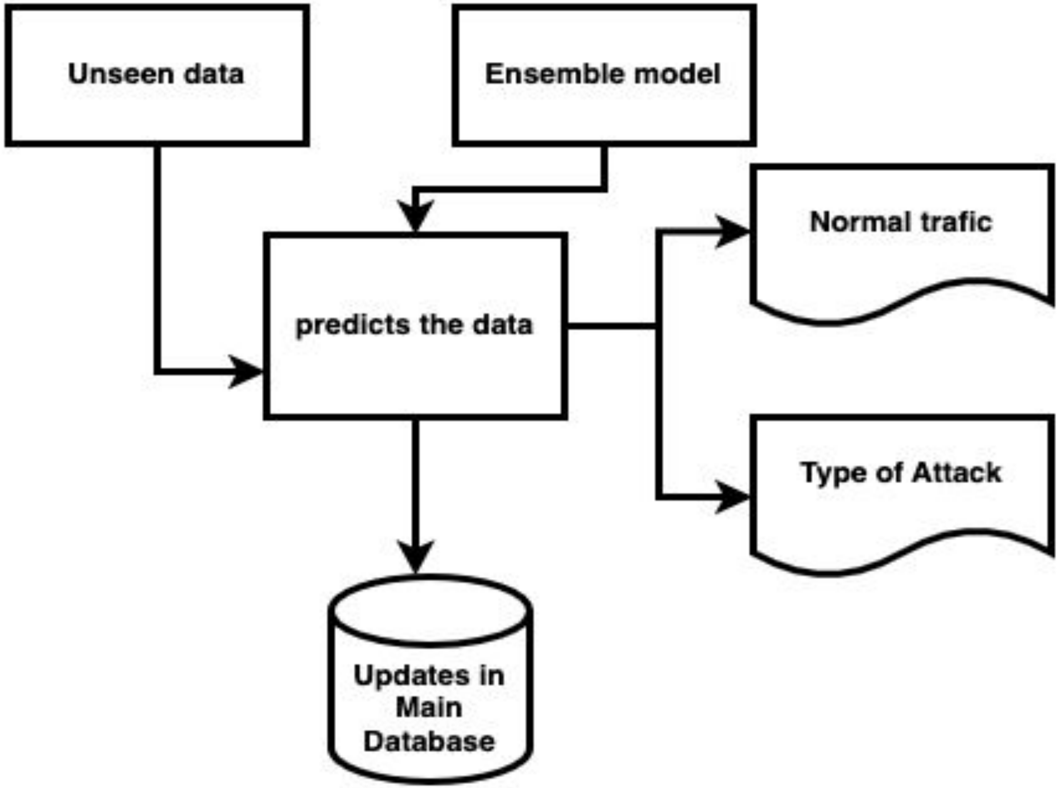


Fig 5.5 RESPONSE PHASE

IMPLEMENTATION DETAILS 30%

Pre-processing techniques:

LABEL ENCODING & REMOVING NAN AND INFINITE VALUES:

```
[6] dff = pd.read_csv('/content/drive/MyDrive/FYP/final_dataset.csv')
```

```
[7] dff = dff.fillna(0)
    dff = dff.replace([np.inf, -np.inf], 1e9)
```

```
[8] col_to_encode = ' Label'
    encoder = LabelEncoder()
    dff[col_to_encode] = encoder.fit_transform(dff[col_to_encode])
```

```
[9] dff[col_to_encode].unique()

    array([ 0,  7, 11,  6,  5,  4,  3,  8, 12, 14, 13,  9,  1, 10,  2])
```

```
[14] dff
```

Total Fwd Packets	Total Backward Packets	Total Length of Fwd Packets	Total Length of Bwd Packets	Fwd Packet Length Max	Fwd Packet Length Min	Fwd Packet Length Mean	Fwd Packet Length Std	...	min_seg_size_forward	Active Mean	Active Std	Active Max	Active Min	Idle Mean	Idle Std	Idle Max	Idle Min	Label
2	0	12	0	6	6	6.000000	0.000000	...	20	0.0	0.0	0	0	0.0	0.0	0	0	0
2	0	12	0	6	6	6.000000	0.000000	...	20	0.0	0.0	0	0	0.0	0.0	0	0	0
7	4	484	414	233	0	69.142857	111.967895	...	20	0.0	0.0	0	0	0.0	0.0	0	0	0
9	4	656	3064	313	0	72.888889	136.153814	...	20	0.0	0.0	0	0	0.0	0.0	0	0	0
9	6	3134	3048	1552	0	348.222222	682.482560	...	20	0.0	0.0	0	0	0.0	0.0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
2	0	12	0	6	6	6.000000	0.000000	...	20	0.0	0.0	0	0	0.0	0.0	0	0	0
2	0	0	0	0	0	0.000000	0.000000	...	32	0.0	0.0	0	0	0.0	0.0	0	0	0
1	1	6	6	6	6	6.000000	0.000000	...	20	0.0	0.0	0	0	0.0	0.0	0	0	0
2	0	248	0	242	6	124.000000	166.877200	...	20	0.0	0.0	0	0	0.0	0.0	0	0	0
1	1	6	6	6	6	6.000000	0.000000	...	20	0.0	0.0	0	0	0.0	0.0	0	0	0

Fig 6.1 LABEL ENCODING

NORMALISATION (MIN MAX SCALAR)

```
[11] # Normalize the data in each column
     features = pd.DataFrame(scaler.fit_transform(features), columns=features.columns)
```

```
[12] # Split the data into training and testing sets
     X_train, X_test, y_train, y_test = train_test_split(features, target, test_size=0.2, random_state=42)
```

```
features
```

	Destination Port	Flow Duration	Total Fwd Packets	Total Backward Packets	Total Length of Fwd Packets	Total Length of Bwd Packets	Fwd Packet Length Max	Fwd Packet Length Min	Fwd Packet Length Mean	Fwd Packet Length Std	...	act_data_pkt_fwd	min_seg_size_forward	Acti Me
0	0.755119	1.333333e-07	0.000005	0.000000	9.302326e-07	0.000000e+00	0.000257	0.002581	0.001010	0.000000	...	0.000005	1.0	
1	0.755119	1.166667e-07	0.000005	0.000000	9.302326e-07	0.000000e+00	0.000257	0.002581	0.001010	0.000000	...	0.000005	1.0	
2	0.001343	5.183333e-06	0.000027	0.000014	3.751938e-05	6.316242e-07	0.009974	0.000000	0.011639	0.015713	...	0.000023	1.0	
3	0.001343	7.433333e-06	0.000036	0.000014	5.085271e-05	4.674629e-06	0.013399	0.000000	0.012269	0.019108	...	0.000033	1.0	
4	0.001343	9.774999e-06	0.000036	0.000021	2.429457e-04	4.650219e-06	0.066438	0.000000	0.058615	0.095779	...	0.000033	1.0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
1530738	0.936033	2.900000e-06	0.000005	0.000000	9.302326e-07	0.000000e+00	0.000257	0.002581	0.001010	0.000000	...	0.000005	1.0	
1530739	0.609577	1.925000e-06	0.000005	0.000000	0.000000e+00	0.000000e+00	0.000000	0.000000	0.000000	0.000000	...	0.000000	1.0	
1530740	0.935408	3.416666e-07	0.000000	0.000003	4.651163e-07	9.153974e-09	0.000257	0.002581	0.001010	0.000000	...	0.000000	1.0	

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Fig 6.2 MIN MAX SCALAR

FEATURE EXTRACTION (SCAE):

```
[ ] # Define the hyperparameters
    input_dim = 78
    hidden_dim_1 = 64
    hidden_dim_2 = 32
    learning_rate = 0.001
    batch_size = 32
    num_epochs = 20
    beta = 1.0  # the coefficient for the contractive penalty term

    # Define the layers of the autoencoder
    input_layer = tf.keras.layers.Input(shape=(input_dim,))
    encoder_1 = tf.keras.layers.Dense(hidden_dim_1, activation="relu")(input_layer)
    encoder_2 = tf.keras.layers.Dense(hidden_dim_2, activation="relu")(encoder_1)
    decoder_1 = tf.keras.layers.Dense(hidden_dim_1, activation="relu")(encoder_2)
    decoder_2 = tf.keras.layers.Dense(input_dim, activation="sigmoid")(decoder_1)

    # Define the model and compile it
    autoencoder = tf.keras.models.Model(inputs=input_layer, outputs=decoder_2)
```

Fig 6.3 AUTO ENCODER

```python
def contractive_loss(y_true, y_pred):
    """Calculates the contractive loss for a given batch of input data."""
    mse = K.mean(K.square(y_true - y_pred), axis=1)
    W = K.variable(value=autoencoder.get_layer('dense_56').get_weights()[0]) # Get the weight matrix of the first hidden layer
    # Compute the jacobian matrix of the hidden layer outputs with respect to the input layer inputs
    h = autoencoder.get_layer('dense_56').output
    dh = h * (1 - h) # Derivative of the sigmoid activation function
    jacobian = dh[:, None] * W.T[None, :, :] # Compute the jacobian matrix
    jacobian = K.sum(jacobian ** 2, axis=(1, 2))
    return mse + 1e-4 * jacobian


autoencoder.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=learning_rate),
                    loss=contractive_loss,
                    metrics=["accuracy"])
es = EarlyStopping(monitor='val_loss', mode='min', verbose=1, patience=15)
mc = ModelCheckpoint('/Users/tharun/Desktop/FYP/DATASET/best_model_CNN.h5', monitor='val_accuracy', mode='max', verbose=1, save_best_only=True)
# Train the model
history = autoencoder.fit(X_train, X_train,
                          epochs=num_epochs,
                          batch_size=batch_size,
                          validation_data=(X_test, X_test),callbacks=[es,mc])
```

Fig 6.4 CONTRACTIVE LOSS FUNCTION

```
Epoch 1/20
38268/38269 [============================>.] - ETA: 0s - loss: 5.2701e-04 - accuracy: 0.3957
Epoch 1: val_accuracy improved from -inf to 0.54809, saving model to /Users/tharun/Desktop/FYP/DATASET/best_model_C
NN.h5
38269/38269 [==============================] - 93s 2ms/step - loss: 5.2701e-04 - accuracy: 0.3957 - val_loss: 1.637
5e-04 - val_accuracy: 0.5481
Epoch 2/20
38262/38269 [============================>.] - ETA: 0s - loss: 1.0424e-04 - accuracy: 0.6519
Epoch 2: val_accuracy improved from 0.54809 to 0.59265, saving model to /Users/tharun/Desktop/FYP/DATASET/best_mode
l_CNN.h5
38269/38269 [==============================] - 112s 3ms/step - loss: 1.0423e-04 - accuracy: 0.6519 - val_loss: 2.32
85e-05 - val_accuracy: 0.5926
Epoch 3/20
38265/38269 [============================>.] - ETA: 0s - loss: 2.3105e-05 - accuracy: 0.6408
Epoch 3: val_accuracy improved from 0.59265 to 0.71753, saving model to /Users/tharun/Desktop/FYP/DATASET/best_mode
l_CNN.h5
38269/38269 [==============================] - 112s 3ms/step - loss: 2.3104e-05 - accuracy: 0.6408 - val_loss: 1.70
70e-05 - val_accuracy: 0.7175
Epoch 4/20
```

```
Epoch 17: val_accuracy did not improve from 0.97603
38269/38269 [==============================] - 98s 3ms/step - loss: 1.2297e-05 - accuracy: 0.8807 - val_loss: 9.928
4e-06 - val_accuracy: 0.8245
Epoch 18/20
38258/38269 [============================>.] - ETA: 0s - loss: 1.2391e-05 - accuracy: 0.8539
Epoch 18: val_accuracy did not improve from 0.97603
38269/38269 [==============================] - 102s 3ms/step - loss: 1.2389e-05 - accuracy: 0.8539 - val_loss: 8.92
45e-06 - val_accuracy: 0.9486
Epoch 19/20
38267/38269 [============================>.] - ETA: 0s - loss: 1.2514e-05 - accuracy: 0.8910
Epoch 19: val_accuracy improved from 0.97603 to 0.99153, saving model to /Users/tharun/Desktop/FYP/DATASET/best_mod
el_CNN.h5
38269/38269 [==============================] - 96s 3ms/step - loss: 1.2514e-05 - accuracy: 0.8910 - val_loss: 1.293
0e-05 - val_accuracy: 0.9915
Epoch 20/20
38268/38269 [============================>.] - ETA: 0s - loss: 1.1610e-05 - accuracy: 0.8798
Epoch 20: val_accuracy did not improve from 0.99153
38269/38269 [==============================] - 98s 3ms/step - loss: 1.1610e-05 - accuracy: 0.8798 - val_loss: 9.542
0e-06 - val_accuracy: 0.9339
```

Fig 6.5 TRAINED SCAE

```
[ ] # Test the model
    test_loss, test_acc = best_model.evaluate(X_test, X_test)
    print(f"Test loss: {test_loss:.4f}")
    print(f"Test accuracy: {test_acc:.4f}")
```

```
9568/9568 [==============================] - 11s 1ms/step - loss: 1.2930e-05 - accuracy: 0.9915
Test loss: 0.0000
Test accuracy: 0.9915
```

```
[ ]
```

```
[ ] # Extract the encoder layers
    encoder_1 = tf.keras.models.Model(inputs=input_layer, outputs=encoder_1)
    encoder_2 = tf.keras.models.Model(inputs=encoder_1.input, outputs=encoder_2)
```

```
[ ] encoded_train = encoder_2.predict(X_train)
    encoded_test = encoder_2.predict(X_test)
```

```
38269/38269 [==============================] - 74s 2ms/step
9568/9568 [==============================] - 10s 1ms/step
```

Fig 6.6 ACCURACY AND PREDICTIONS

LSTM MODEL:

```
[ ] model3 = models.Sequential()
model3.add(layers.LSTM(50, input_shape = (32,1), activation = 'tanh', return_sequences = True, recurrent_activation='sigmoid', recurrent_dropout = 0.0, unro
model3.add(layers.Dropout(0.15))
model3.add(layers.LSTM(50, activation = 'tanh', return_sequences = True,recurrent_activation='sigmoid',recurrent_dropout = 0.0,unroll=False ,use_bias=True))
model3.add(layers.Dropout(0.25))
model3.add(layers.LSTM(50, activation = 'tanh', return_sequences = True,recurrent_activation='sigmoid',recurrent_dropout = 0.0,unroll=False ,use_bias=True))
model3.add(layers.Dropout(0.35))
model3.add(layers.LSTM(50, activation = 'tanh',recurrent_activation='sigmoid',recurrent_dropout = 0.0,unroll=False ,use_bias=True))
model3.add(layers.Dropout(0.45))
model3.add(layers.Flatten())
model3.add(layers.Dense(50,activation = 'relu'))
model3.add(layers.Dropout(0.04))
model3.add(layers.Dense(15,activation = 'softmax'))
optimizer = tf.keras.optimizers.Adam(learning_rate=1e-5)
model3.compile(loss = tf.keras.losses.SparseCategoricalCrossentropy(),
              optimizer = 'adam',
              metrics = ['accuracy'])
model3.summary()
```

Fig 6.7 LSTM MODEL

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 32, 50)            10400

 dropout (Dropout)           (None, 32, 50)            0

 lstm_1 (LSTM)               (None, 32, 50)            20200

 dropout_1 (Dropout)         (None, 32, 50)            0

 lstm_2 (LSTM)               (None, 32, 50)            20200

 dropout_2 (Dropout)         (None, 32, 50)            0

 lstm_3 (LSTM)               (None, 50)                20200

 dropout_3 (Dropout)         (None, 50)                0

 flatten (Flatten)           (None, 50)                0

 dense (Dense)               (None, 50)                2550

 dropout_4 (Dropout)         (None, 50)                0

 dense_1 (Dense)             (None, 15)                765

=================================================================
Total params: 74,315
Trainable params: 74,315
Non-trainable params: 0
_________________________________________________________________
```

Fig 6.8 MODEL SUMMARY

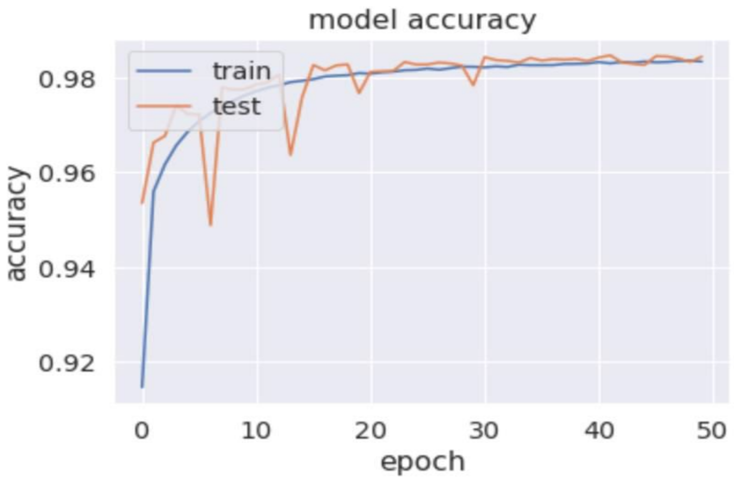
```
es = EarlyStopping(monitor='val_loss', mode='min', verbose=1, patience=15)
mc = ModelCheckpoint('/Users/tharun/Desktop/FYP/DATASET/best_model_LSTM1.h5', monitor='val_accuracy', mode='max', verbose=1, save_best_only=True)
# Train the model
history = model3.fit(fea_train.reshape(fea_train.shape[0], fea_train.shape[1], 1), tar_train, validation_data=(fea_test, tar_test), epochs=50, batch_size=12
```

```
Epoch 1/50
9566/9568 [============================>.] - ETA: 0s - loss: 0.2482 - accuracy: 0.9146
Epoch 1: val_accuracy improved from -inf to 0.95349, saving model to /Users/tharun/Desktop/FYP/DATASET/best_model_LSTM1.h5
9568/9568 [==============================] - 136s 14ms/step - loss: 0.2482 - accuracy: 0.9146 - val_loss: 0.1157 - val_accuracy: 0.9535
Epoch 2/50
9567/9568 [============================>.] - ETA: 0s - loss: 0.1163 - accuracy: 0.9560
Epoch 2: val_accuracy improved from 0.95349 to 0.96629, saving model to /Users/tharun/Desktop/FYP/DATASET/best_model_LSTM1.h5
9568/9568 [==============================] - 135s 14ms/step - loss: 0.1163 - accuracy: 0.9560 - val_loss: 0.0882 - val_accuracy: 0.9663
Epoch 3/50
9567/9568 [============================>.] - ETA: 0s - loss: 0.0991 - accuracy: 0.9617
Epoch 3: val_accuracy improved from 0.96629 to 0.96771, saving model to /Users/tharun/Desktop/FYP/DATASET/best_model_LSTM1.h5
9568/9568 [==============================] - 134s 14ms/step - loss: 0.0991 - accuracy: 0.9617 - val_loss: 0.0783 - val_accuracy: 0.9677
Epoch 4/50
9567/9568 [============================>.] - ETA: 0s - loss: 0.0903 - accuracy: 0.9657
Epoch 4: val_accuracy improved from 0.96771 to 0.97419, saving model to /Users/tharun/Desktop/FYP/DATASET/best_model_LSTM1.h5
9568/9568 [==============================] - 141s 15ms/step - loss: 0.0903 - accuracy: 0.9657 - val_loss: 0.0693 - val_accuracy: 0.9742
Epoch 5/50
9567/9568 [============================>.] - ETA: 0s - loss: 0.0842 - accuracy: 0.9686
Epoch 5: val_accuracy did not improve from 0.97419
9568/9568 [==============================] - 140s 15ms/step - loss: 0.0842 - accuracy: 0.9686 - val_loss: 0.0720 - val_accuracy: 0.9723
Epoch 6/50
9568/9568 [==============================] - ETA: 0s - loss: 0.0794 - accuracy: 0.9708
Epoch 6: val_accuracy did not improve from 0.97419
9568/9568 [==============================] - 142s 15ms/step - loss: 0.0794 - accuracy: 0.9708 - val_loss: 0.0679 - val_accuracy: 0.9723
Epoch 7/50
9568/9568 [==============================] - ETA: 0s - loss: 0.0757 - accuracy: 0.9726
Epoch 7: val_accuracy did not improve from 0.97419
9568/9568 [==============================] - 143s 15ms/step - loss: 0.0757 - accuracy: 0.9726 - val_loss: 0.1153 - val_accuracy: 0.9488
Epoch 8/50
9567/9568 [============================>.] - ETA: 0s - loss: 0.0725 - accuracy: 0.9740
Epoch 8: val_accuracy improved from 0.97419 to 0.97801, saving model to /Users/tharun/Desktop/FYP/DATASET/best_model_LSTM1.h5
9568/9568 [==============================] - 132s 14ms/step - loss: 0.0725 - accuracy: 0.9740 - val_loss: 0.0618 - val_accuracy: 0.9780
Epoch 9/50
```

```
[ ]
9568/9568 [==============================] - 138s 14ms/step - loss: 0.0458 - accuracy: 0.9833 - val_loss: 0.0423 - val_accuracy: 0.9843
Epoch 42/50
9566/9568 [============================>.] - ETA: 0s - loss: 0.0461 - accuracy: 0.9831
Epoch 42: val_accuracy improved from 0.98436 to 0.98475, saving model to /Users/tharun/Desktop/FYP/DATASET/best_model_LSTM1.h5
9568/9568 [==============================] - 132s 14ms/step - loss: 0.0461 - accuracy: 0.9831 - val_loss: 0.0411 - val_accuracy: 0.9847
Epoch 43/50
9568/9568 [==============================] - ETA: 0s - loss: 0.0455 - accuracy: 0.9834
Epoch 43: val_accuracy did not improve from 0.98475
9568/9568 [==============================] - 141s 15ms/step - loss: 0.0455 - accuracy: 0.9834 - val_loss: 0.0438 - val_accuracy: 0.9833
Epoch 44/50
9565/9568 [============================>.] - ETA: 0s - loss: 0.0459 - accuracy: 0.9832
Epoch 44: val_accuracy did not improve from 0.98475
9568/9568 [==============================] - 131s 14ms/step - loss: 0.0459 - accuracy: 0.9832 - val_loss: 0.0473 - val_accuracy: 0.9829
Epoch 45/50
9567/9568 [============================>.] - ETA: 0s - loss: 0.0453 - accuracy: 0.9834
Epoch 45: val_accuracy did not improve from 0.98475
9568/9568 [==============================] - 140s 15ms/step - loss: 0.0453 - accuracy: 0.9834 - val_loss: 0.0473 - val_accuracy: 0.9827
Epoch 46/50
9566/9568 [============================>.] - ETA: 0s - loss: 0.0455 - accuracy: 0.9833
Epoch 46: val_accuracy did not improve from 0.98475
9568/9568 [==============================] - 132s 14ms/step - loss: 0.0455 - accuracy: 0.9833 - val_loss: 0.0413 - val_accuracy: 0.9846
Epoch 47/50
9565/9568 [============================>.] - ETA: 0s - loss: 0.0453 - accuracy: 0.9833
Epoch 47: val_accuracy did not improve from 0.98475
9568/9568 [==============================] - 139s 14ms/step - loss: 0.0453 - accuracy: 0.9833 - val_loss: 0.0414 - val_accuracy: 0.9845
Epoch 48/50
9567/9568 [============================>.] - ETA: 0s - loss: 0.0448 - accuracy: 0.9836
Epoch 48: val_accuracy did not improve from 0.98475
9568/9568 [==============================] - 130s 14ms/step - loss: 0.0448 - accuracy: 0.9836 - val_loss: 0.0419 - val_accuracy: 0.9841
Epoch 49/50
9565/9568 [============================>.] - ETA: 0s - loss: 0.0446 - accuracy: 0.9836
Epoch 49: val_accuracy did not improve from 0.98475
9568/9568 [==============================] - 132s 14ms/step - loss: 0.0446 - accuracy: 0.9836 - val_loss: 0.0436 - val_accuracy: 0.9834
Epoch 50/50
9566/9568 [============================>.] - ETA: 0s - loss: 0.0447 - accuracy: 0.9834
Epoch 50: val_accuracy did not improve from 0.98475
9568/9568 [==============================] - 136s 14ms/step - loss: 0.0447 - accuracy: 0.9834 - val_loss: 0.0424 - val_accuracy: 0.9845
```

Fig 6.9 TRAINED LSTM MODEL

```
[ ] sns.set_context('notebook', font_scale= 1.3)
    plt.plot(history.history['accuracy'])
    plt.plot(history.history['val_accuracy'])
    plt.title('model accuracy')
    plt.ylabel('accuracy')
    plt.xlabel('epoch')
    plt.legend(['train', 'test'], loc='upper left')
    plt.show()
```




```
[ ] model3.save('/content/drive/MyDrive/FYP/DATASET/LSTM.h5')
```

Fig 6.10 LSTM MODEL ACCURACY

```
[ ]  # Apply the softmax activation function to the output tensor
     from scipy.special import softmax
     pred_probs = softmax(lstm_pred1, axis=0)

     # Get the class with the highest probability
     #pred_class = np.argmax(pred_probs, axis=0)
     sns.set_context('notebook', font_scale= 1.3)
     fig, ax = plt.subplots(1, 2, figsize = (25,  8))
     ax1 = plot_confusion_matrix(tar_test, lstm_pred1, ax= ax[0], cmap= 'YlGnBu')
     #ax2 = plot_roc(tar_test, pred_class, ax= ax[1], plot_macro= False, plot_micr
```

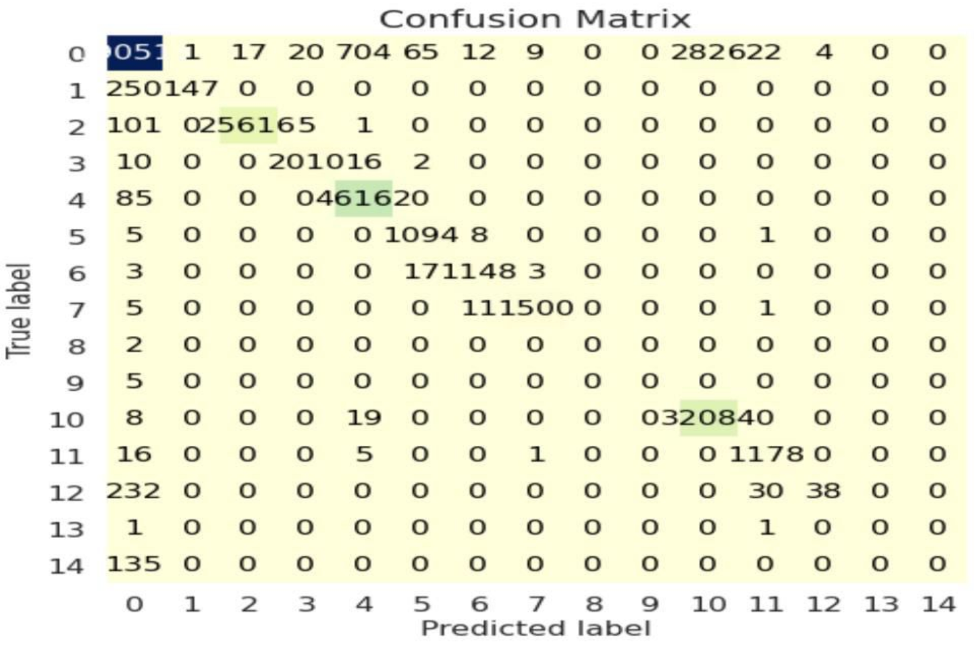


Fig 6.11 LSTM MODEL CONFUSION MATRIX

```
[ ] # Compute initial ensemble accuracy
    dt_pred1 = dt.predict(fea_test)
    lstm_pred_prob = model3.predict(fea_test)
    lstm_pred1 = np.argmax(lstm_pred_prob, axis=1)

    9568/9568 [==============================] - 54s 5ms/step

[ ] # Calculate precision and recall
    precision, recall, _, _ = precision_recall_fscore_support(tar_test, lstm_pred1, average='weighted')

    # Display or save the precision and recall
    print(f'Precision: {precision:.3f}, Recall: {recall:.3f}')

    Precision: 0.985, Recall: 0.985
```

Add text cell

Fig 6.12 PRECISION AND RECALL OF LSTM MODEL

DECISION TREE:

```
[ ] from keras.models import load_model
    model3=load_model('/content/drive/MyDrive/FYP/DATASET/LSTM.h5')
```

```
[ ] dt = DecisionTreeClassifier(random_state=42)
    dt.fit(fea_train,tar_train)
```

```
DecisionTreeClassifier(random_state=42)
```

```
[ ] dt_pred_test=dt.predict(fea_test)
```

```
[ ] accuracy1 = accuracy_score(tar_test, dt_pred_test)
    accuracy1
```

```
0.994685594269457
```

```
[ ] # Calculate precision and recall
    precision, recall, _, _ = precision_recall_fscore_support(tar_test, dt_pred_test, average='weighted')

    # Display or save the precision and recall
    print(f'Precision: {precision:.3f}, Recall: {recall:.3f}')
```

```
Precision: 0.995, Recall: 0.995
```

Fig 6.13 PRECISION AND RECALL OF DECISION TREE MODEL

```python
y_prob = dt.predict_proba(fea_test)
sns.set_context('notebook', font_scale= 1.3)
fig, ax = plt.subplots(1, 2, figsize = (25,  8))
ax1 = plot_confusion_matrix(tar_test, dt_pred_test, ax= ax[0], cmap= 'YlGnBu')
ax2 = plot_roc(tar_test, y_prob, ax= ax[1], plot_macro= False, plot_micro= False, cmap= 'winter')
```

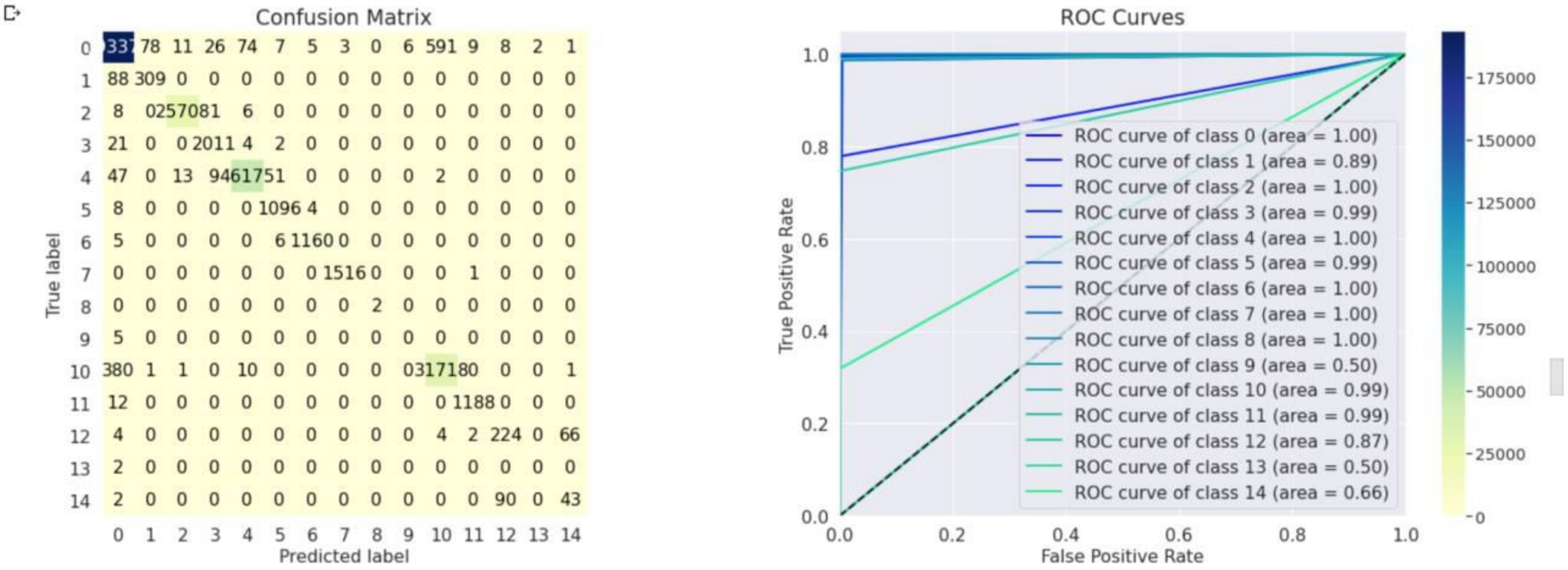


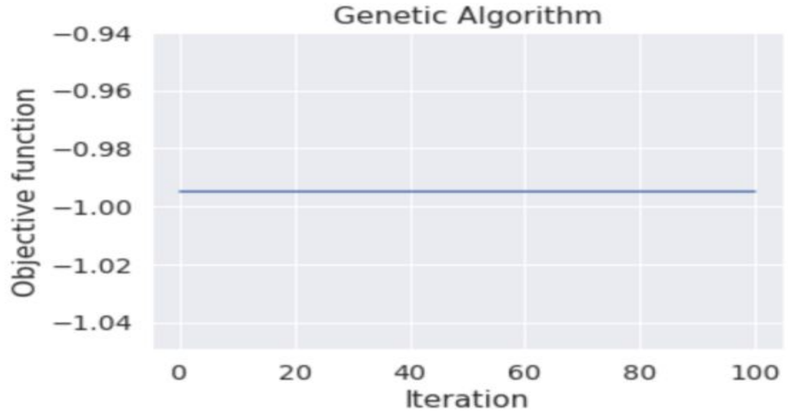
Fig 6.14 CONFUSION MATRIX AND ROC CURVE OF DECISION TREE MODEL

ENSEMBLE MODEL:

```
import numpy as np
from geneticalgorithm import geneticalgorithm as ga

# Define the fitness function that calculates the accuracy of the ensemble model
def fitness_function(weights):
    # Combine the predictions using the weights
    weighted_pred = weights[0] * dt_pred1 + weights[1] * lstm_pred1

    # Round the prediction to the nearest integer
    final_pred = np.round(weighted_pred)

    # Calculate the accuracy of the final prediction
    accuracy = accuracy_score(tar_test, final_pred)

    # Return the negative accuracy (since the genetic algorithm minimizes the objective function)
    return -accuracy

# Define the bounds for the weights (between 0 and 1)
bounds = [(0, 1), (0, 1)]
bounds = np.array(bounds)
algorithm_param = {'max_num_iteration': 100,\
                   'population_size':100,\
                   'mutation_probability':0.1,\
                   'elit_ratio': 0.01,\
                   'crossover_probability': 0.5,\
                   'parents_portion': 0.3,\
                   'crossover_type':'uniform',\
                   'max_iteration_without_improv':None}
# Create the genetic algorithm object
ga_model = ga(function=fitness_function, dimension=2, variable_type='real', variable_boundaries=bounds, algorithm_parameters=algorithm_param)
# Run the genetic algorithm for 100 generations with a population size of 20
ga_model.run()
# Get the best weights found by the genetic algorithm
weights = ga_model.best_variable
```

Fig 6.15 GENETIC ALGORITHM

```
The best solution found:
[0.98098415 0.0231155 ]

Objective function:
-0.994685594269457
```




```
[ ] ensemble_pred1 = np.average([dt_pred1, lstm_pred1], axis=0, weights=weights)
    initial_score = np.mean(ensemble_pred1 == tar_test)
    print("Initial ensemble accuracy: {:.2f}%".format(initial_score*100))
```

```
Initial ensemble accuracy: 97.77%
```

```
[ ] y_pred_ensemble = np.array([np.argmax(np.bincount([dt_pred1[i], lstm_pred1[i]])) for i in range(len(dt_pred1))])
```

Fig 6.16 ACCURACY AND PREDICTION OF ENSEMBLE MODEL

```
[ ]  sns.set_context('notebook', font_scale= 1.3)
     fig, ax = plt.subplots(1, 2, figsize = (25,  8))
     ax1 = plot_confusion_matrix(tar_test, y_pred_ensemble, ax= ax[0], cmap= 'YlGnBu'
```

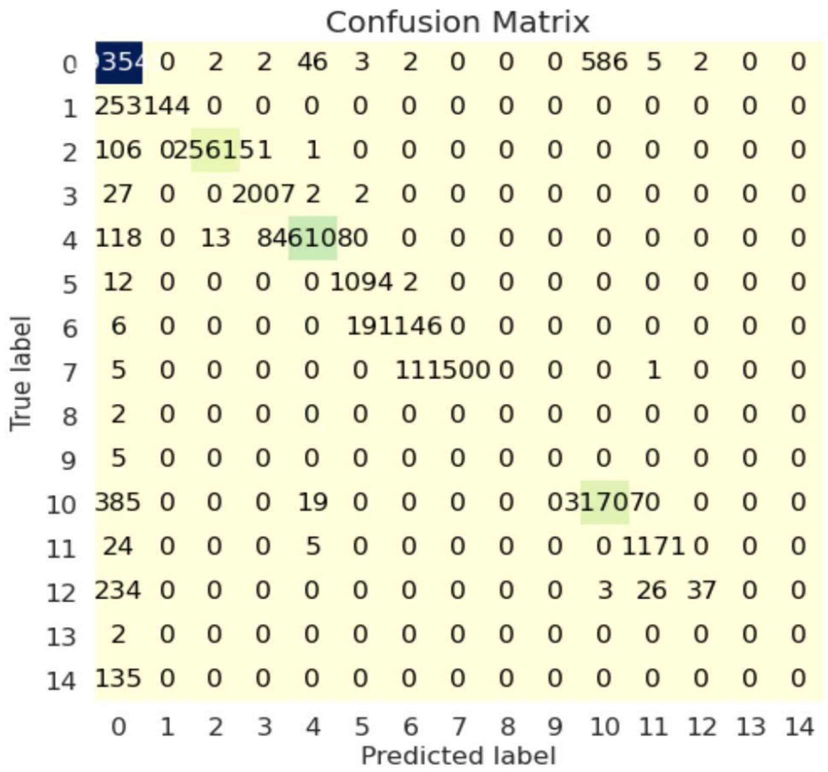


Fig 6.17 CONFUSION MATRIX OF ENSEMBLE MODEL

METRICS FOR EVALUATION

THRESHOLD METRICS:

- **Classification Rate (CR):** Classification rate is a metric that measures the accuracy of a classifier, or how well it can predict the correct class label of a data point.

Classification Rate = Number of Correct Predictions / Total Number of Predictions

- **F Measure (FM):** F-measure is a metric used to measure the accuracy of a classification model. It is a harmonic mean between precision and recall.

F-measure = 2 * (Precision * Recall) / (Precision + Recall)

RANKING METRICS:

- **Accuracy:** It is the percentage of correctly predicted labels out of all instances in the dataset.

  Accuracy = (Number of Correct Predictions) / Total Number of Predictions

- **Recall:** Recall measures the proportion of actual positive instances that are correctly identified by the model as positive.

  Recall = True Positives / (True Positives + False Negatives)

- **Precision (PR):** Precision is a measure of the accuracy of a measurement or a system that produces measurements.

Precision = (Number of correctly estimated measurements / Total number of measurements) x 100

- **Area Under ROC Curve (AUC):** AUC, or Area Under the Receiver Operating Characteristic Curve, is a metric used to measure the performance of a binary classifier. It is a way to measure the accuracy and power of a classifier. AUC measures the area under the ROC curve, which is a graph of the true positive rate against the false positive rate.

$$\mathbf{AUC = \int_{0}^{1} ROC(t)dt}$$

PROBABILITY METRICS:

- **Root Mean Square Error (RMSE):** Root Mean Square Error (RMSE) is a measure of how well a model fits a dataset. It is the average of the squared differences between the observed values and the predicted values.

$$\mathbf{RMSE = \sqrt{(\sum (predicted - observed)^2 / n)}}$$

TEST CASES

TEST CASE	DESCRIPTION
1	Testing the model’s ability to detect multiple attacks
2	Testing the model’s detection of attacks from unknown source
3	Test the model’s performance over different types of data
4	Test the scalability of the model to handle large number of traffic

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