Enhancing Cloud Security with Deep Learning - An ANN Approach for Cyber Threat Detection

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***Abstract*—As cloud computing becomes more and more fundamental to digital infrastructure, safety features are important to state the cyber threats. This paper presents an technique to improving cloud protection using deep gaining knowledge mainly Artificial Neural Networks (ANNs). We leverage ANN algorithms along with Levenberg-Marquardt, Scaled Conjugate Gradient, and Bayesian Regularization to increase an advanced hazard detection gadget able to figuring out complicated attack patterns in cloud environments. Our research focuses on detecting various cyber threats, along with malware, phishing, and Distributed Denial of Service (DDoS) attacks.Finally, the incorporation of ANNs and other deep learning techniques can be advantageous to cloud security frameworks as they offer a novel approach to cyberthreat identification. Our study demonstrates how ANN-based models for quick and efficient threat identification can improve cloud security.**

***Index Terms*—Cloud computing, cyber threat detection, Deep Learning, Levenberg-Marquardt algorithm, scale conjugate gradient, Bayesian Regularization, Artificial Neural Networks (ANNs).**

I. Introduction

The emergence of cloud computing has fundamentally altered how people and organizations store, manage, and access information. It provides previously unheard of scale and flexibility[1]. Because cloud systems are centralised, they are attractive targets for cybercriminals, who are always coming up with more complex and varied ways to take advantage of weaknesses.As a result, new adaptive, intelligent security responses that can catch and neutralize threats in real time are not readily available. Ability to improve cloud system cyber security. In particular, artificial neural networks (ANNs) have shown remarkable ability to detect and identify complex patterns in large data sets[2].They are particularly adept at both known and unknown threats because of their ability to adapt and learn from past attacks[2]. This paper investigates the application of deep mastering strategies, that specialize in ANNs[2], to decorate cloud safety through superior cyber threat detection.

II. Literature Review

In addition to providing flexibility, scalability, and performance comparable to standard not exceptional performance, cloud computing also adds security risks such as virus attacks, insider threats, and data breaches[3]. Unauthorised access to sensitive cloud records is one kind of a data breach that can cause harm to one's finances and reputation. Insider threats originate from criminal clients who abuse their access to steal data or interfere with business operations. Traditional protection capabilities, like firewalls and antivirus software, are regularly inadequate to cope with those evolving threats as they will be inclined to be reactive and might not discover superior or zero-day attacks in real-time [3].Deep mastering, a subset of model studying, shows great capability in improving cybersecurity. Models like Artificial Neural Networks (ANNs)[2] can pick out complex styles in massive datasets, making them well-suitable for detecting anomalies and predicting functionality threats.

III. Data Collection

Data can be collected from datasets available on Kaggle.com. The datasets contain data on cyber threats, system logs, network traffic, malware detection, intrusion detection, and anamoly detection.CICIDS 2017[4],this dataset covers a extensive range of community attack situations. UNSW-NB15[4],this dataset also provides well known records, which is to differentiate malicious packages from malicious programs.NSL-KDD[4],this is a received dataset name of intrusion detection,it is optimized to eliminate unnecessary records,making it a reliable method of testing.

IV. Preprocessing

Preprocessing can be done in two steps i.e, handling null values and normalization. During the normalization process, we must choose which category data to convert to numerical data utilizing label or one hot encoding[5].

A. Label Encoding

If a categorical feature (Xj) has (n) unique categories, label encoding maps each category to a unique integer value. This can be represented as:

$$X_j^{(\text{encoded})} = f(X_j) \tag{1}$$

Where f is a bijective function mapping categories to integers.

B. Feature Scaling

For feature scaling using standardization (z-score normalization), the formula applied to each feature Xj is:

$$X_i^{(\text{scaled})} = \frac{X_i - \mu_i}{\sigma_i} \tag{2}$$

Where:

- μ_i is the mean of feature i in the training set.
- σ_i is the standard deviation of feature i in the training set.

V. Proposed ANN Model

To decorate cloud protection the use of deep getting to know through an Artificial Neural Network (ANN) method.This begins with the cautious selection and instruction of facts from the significant CICIDS 2017 and UNSW-NB15 datasets. Given the large quantity of records, sampling 10percent of the preprocessed dataset. The data must be divided into training, testing, and validation sets. Thirty percent of the data is for testing and validation, while the remaining seventy percent is for training.The ANN model can be trained by using the three algorithms: Levenberg-Marquardt,Scale conjugate gradient and Bayesian Regularization algorithms.

A. Levenberg-Marquart algorithm:

This optimization method combines gradient descent and Gauss-Newton method dynamically determines teaching Productivity.It can be defined as:

$$\theta_{k+1} = \theta_k - \left[J^T(\theta_k)J(\theta_k) + \lambda I\right]^{-1} J^T(\theta_k)r(\theta_k) \tag{3}$$

Where:

- θ_k represents the parameters at iteration k
- $J(\theta_k)$ is the Jacobian matrix of partial derivatives
- $r(\theta_k)$ is the residual vector
- λ is the damping factor
- I is the identity matrix

TABLE I
COMPARING THE ANN MODEL WITH OTHER MODELS

SNo	Model	Accuracy
1	ANN	90.20
2	CNN	86.58
3	RNN	87.84
4	LSTM	79.00
5	AutoEncoders	86.01
6	SVM (Original)	84.74
7	SVM (Encoded)	84.95

B. Bayesian Regularization:

Bayesian Regularization employs a probabilistic framework around the model training procedure and is useful when dealing with neural networks, mainly to avoid model overfitting. The cost function E in Bayesian Regularization can be represented as:

$$E = \alpha E_D + \beta E_W \tag{4}$$

where:

- E is the total cost function.
- E_D is the data error term.
- E_W is the weight regularization term.
- α and β are regularization parameters controlling the trade-off between the error term and the regularization term.

C. Scale Conjugate Gradient Algorithm:

This technique is a variant of the conjugate gradient technique, scaled to improve convergence pace and stability. The key formula representing the Scaled Conjugate Gradient (SCG) algorithm in a single expression for updating the weights in a neural network is:

$$\mathbf{W}_{k+1} = \mathbf{W}_k + \lambda_k \mathbf{P}_k \tag{5}$$

where:

- $\mathbf{W}_k$ is the current weight vector at iteration k.
- λ_k is the step size (scaling factor) determined by the algorithm.
- $\mathbf{P}_k$ is the search direction.

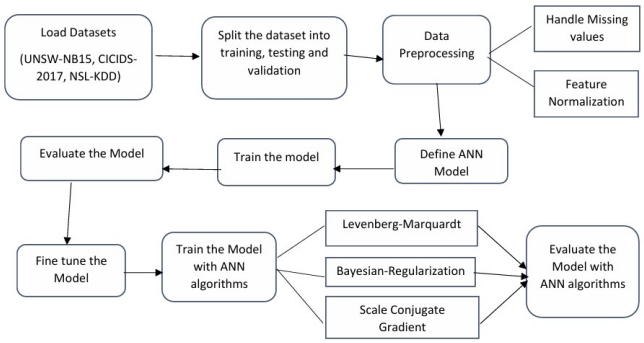

Fig. 1. Proposed Artificial Neural Networks Model Architecture

D. Feed-forward Neural Network:

A feed-forward neural network with L layers can be represented as a series of matrix multiplications and activation functions.For each layer l from 1 to L:

$$c^{[l]} = g^{[l]}(W^{[l]} \cdot c^{[l-1]} + d^{[l]}) \tag{6}$$

where:

- $c^{[l]}$ is the activation of layer l,
- $W^{[l]}$ and $d^{[l]}$ are the weight matrix and bias vector for layer l,
- $g^{[l]}$ is the activation function (e.g., ReLU, sigmoid).

VI. Algorithm for the Proposed Model

A. Preparation of Information:

• The Collection of Data Set and its separation into training, test, and validation subsets are explained in the first subsection. Bring in the datasets for CICIDS 2017 and UNSW-NB15.

• Missing Data: Complete the incomplete data on the data set, usually by using the mean in the numeric columns.

• Categorical features: Convert categorical values into numerical values using label encoding and other such features.

B. Model Definition:

The Articulation of the Neural Network:

• Input Layer: The number of features in the dataset corresponds to the number of input nodes.

• Hidden Layers: Initialize one or several hidden layers, specifying how many neurons and which activation function will be applied (for example ReLU).

• Output Layer: In the case of a binary classification problem, the output layer is made up of a single neuron and has sigmoid activation.

C. Model Compilation:

• Optimizer: Apply any of the optimizing algorithm to find the minima of the loss, for instance Adam optimizer.

• Loss Function: In the case of binary classification problems, the loss function will employ the use of binary cross entropy.

• Metrics: Select the accuracy as the intended performance metric for the model evaluation.

D. Model Training:

• Fit the Model: Execute the training of the artificial neural networks by the training set for a diverse number of epochs and batch size. In the course of this training, a hold-out sample is employed to measure the efficiency of the model on an unseen sample.

E. Model Evaluation:

• Evaluate the Model: Conduct the evaluation of the constructed model on the defining test set to assess the degree of accuracy in the tested model.

F. Model Output:

• Display the Accuracy: The accuracy is expressed as a percentage where correctly classified instances make up a fraction of the test set.

G. Save the Model:

• Saving the trained model: Saving the complete model comprising architecture, defined loss functions and optimizer states makes comprehensive use of the Keras framework.

H. Display the Model Architecture:

• Summary of the Model: Features of the model architecture are summarized suggesting the layers, output shapes and number of parameters.

I. Fine-Tune the Model:

• Modify Hyperparameters: Model performance optimization can be done by changing the learning rate, optimizer type, number of neurons, number of layers, or activation functions among others.

• Retrain Specific Layers: The entire model can also be retrained or modified by re-configuring selectively some layers in relation to fine-tuning.

• Recompile and Retrain: If alteration of the model has occurred, it is recompiled and is re-trained on the available data set.

• Evaluate Post Fine-Tuning: Finally, the model is once again compared to the test set with the intention of verifying how much improvement has been achieved.

VII. Performance Evaluation

The following graphs and tables are the performance metrics used in our ANN model.

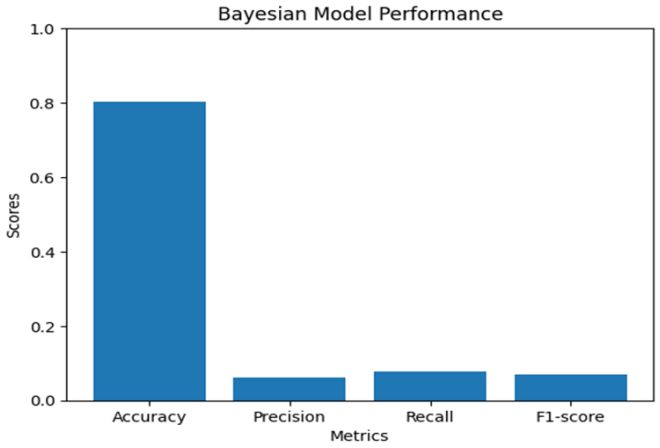

Fig. 2. Performance metrics for ANN Model

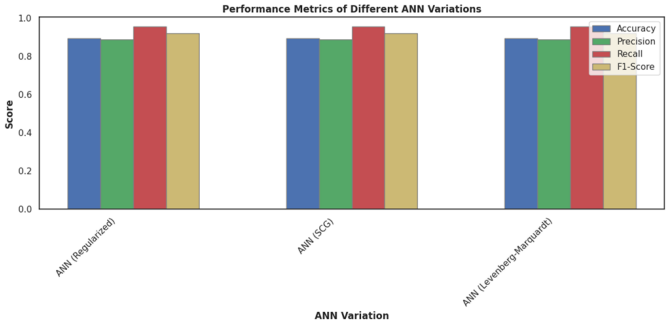

Fig. 3. Metrics for the algorithms used in ANN Model

A. Binary Conversion

The model's output is a probability value, which is converted to a binary prediction based on a threshold of 0.5. It is defined as:

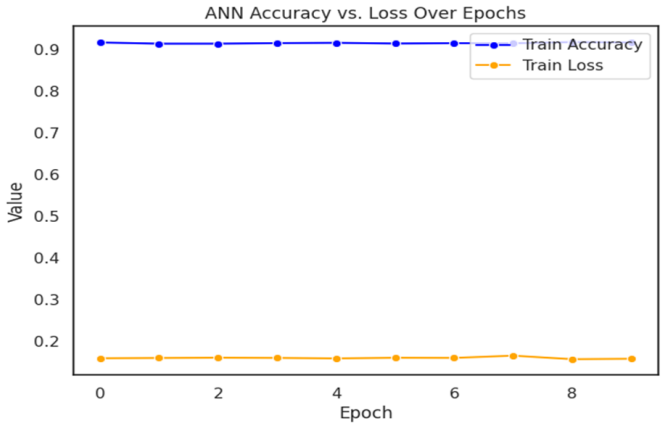

Fig. 4. UNSW-NB15 accuracy versus Loss

$$y_{\text{pred\_binary}} = \begin{cases} 1 & \text{if } y_{\text{pred}} > 0.5 \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

where y_{pred} is the predicted probability.

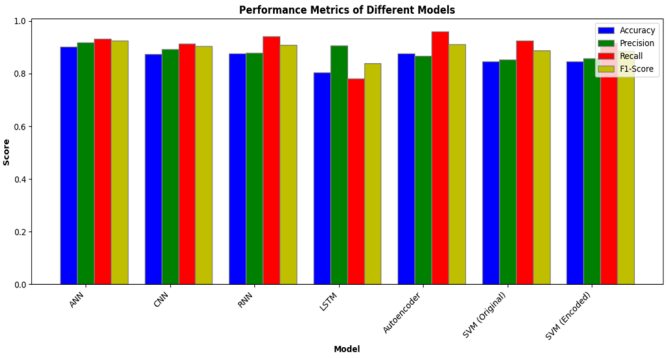

Fig. 5. Performance metrics for the models

TABLE II
DATASET INFORMATION(UNSW-NB15)

SNo	Data	Total Records
1	Training data	18036 (70Percent)
2	Testing data	3866 (15Percent)
3	Validation data	3865 (15Percent)
4	Total records	25767 (100Percent)

TABLE III
INFORMATION ABOUT THE MODELS IN UNSW-NB15

Model	ANN	CNN	RNN	LSTM
Total Params	13,253	99,269	19,013	57,029
Trainable Params	4,417	33,089	6,337	19,009
Non-trainable params	0	0	0	0
Optimizer params	8,836	66,180	12,676	38,020
Accuracy	90.12	87.30	87.69	80.44

The UNSW and CICIDS are both used for implementing and for validation. In table-4 ,it describes that the number of

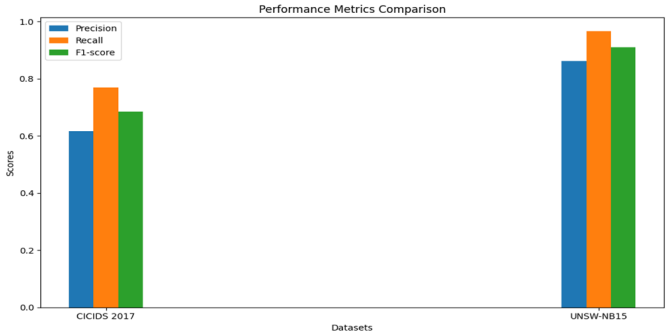

Fig. 6. Comparsion of performance metrics for the both datasets UNSW and CICIDS

training records are 18000 and testing and validation records are 3000 each[6]. Now both the datasets are trained with the ANN model after that we compare with the other models. We can compare with the other models ANN gives best results than other models. ANN model contains the training parameters of 13,253 and total number of optimizer params is 8,836 is shown in table-3[6]. This comparison highlights the ANN's superior effectiveness in this particular task, while also underscoring the varying performance of different models based on their parameter configurations[6].

VIII. COMPARATIVE ANALYSIS

Comparing our ANN model with other models like CNN,RNN, LSTM, Auto encoders.our model gives the best results compared with other models.

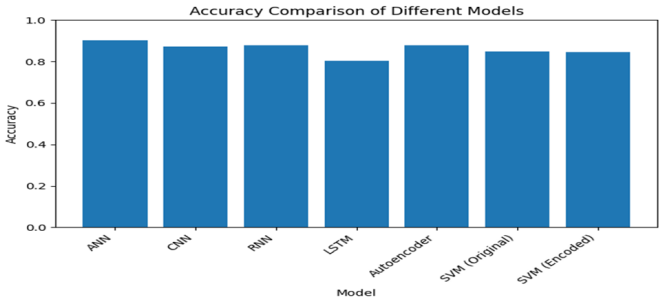

Fig. 7. Comparing ANN with the other models

TABLE IV
ACCURARIES OF BOTH DATASETS

SNo	Dataset	Model Accuracy
1	UNSW-NB15	90.12
2	CICIDS-2017	80.18

To conclude, the study demonstrated that deep learning techniques especially, an improved variation of artificial neural networks employing algorithms like SCG ,LM and BR, can be used to advance cloud security G2 and adjustments of hyperparameters and datasets integration (UNSW-NB15 and CICIDS

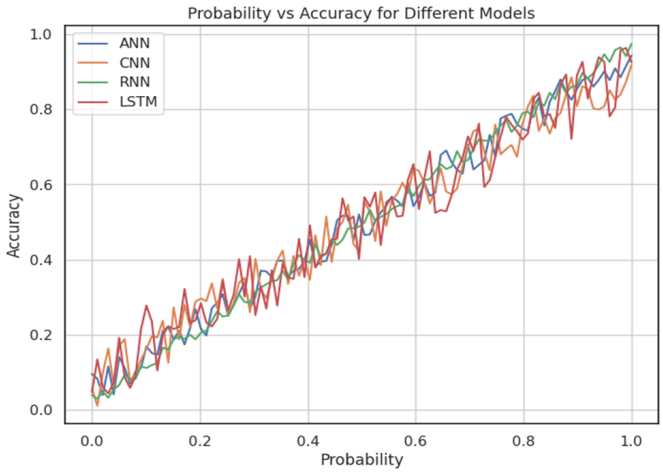

Fig. 8. Probability vs Accuracy for different models

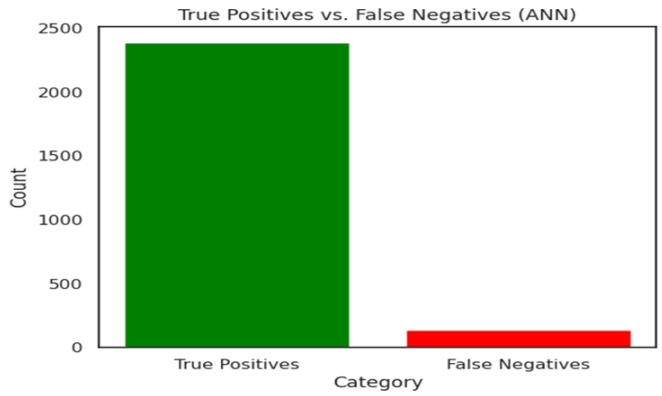

Fig. 9. True Positives vs False Negatives for the ANN model

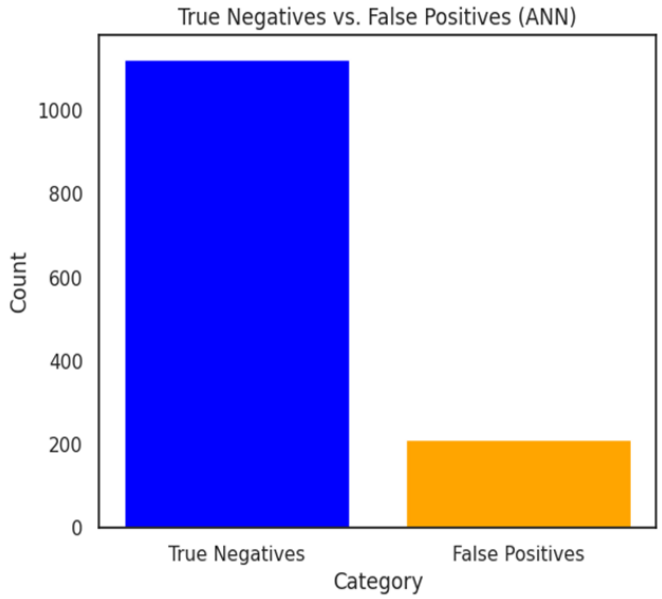

Fig. 10. True Negatives vs False Positives for the ANN model

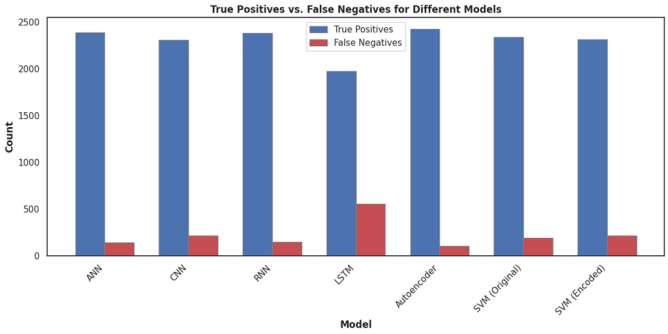

Fig. 11. Tp vs FN of ANN model with other models

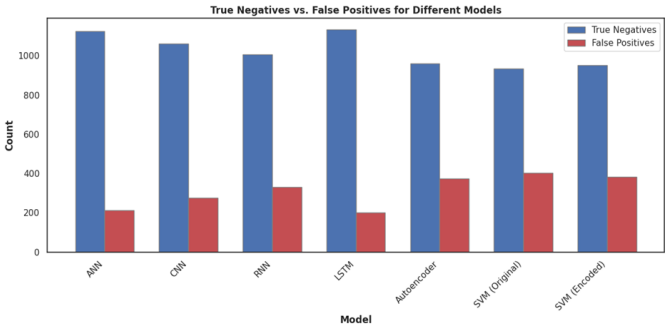

Fig. 12. TN vs FP of ANN model with other models

2017), the model reached an impressive threat detection accuracy, indicating its suitability for real-time threat detection and embedding into multilayer cloud security systems[6].

IX. Result

This paper developed an effective intelligence based model to enhance cloud security through the detection of cyber attacks. By using advanced training techniques such as Levenberg-Marquardt, scale conjugate gradient and Bayesian Regularization, the study was able to achieve improvements in detection of accuracy when validated on UNSW-NB15 and CICIDS 2017 datasets. The paper stressed the importance of algorithm selection and hyper-parameter tuning while aiming at enhancing the performance of the ANN architecture. In addition, further comparative analysis with other models have as well confirmed the ability of the ANN in performing real-time threat detection in clouds. This study shows that the construction of ANNs in today's environment, with all the tools and equipment of cloud security, will be able to effectively cope with the new type of cyber threats. It constitutes a flexible and effective partial solution in the fighting of future advanced threats targeting largely adopted cloud services.

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