A Novel Method for Detecting Liver Tumors combining Machine Learning with Medical Imaging in CT Scans using ResUNet

1st P. Manjula
Department of Logicnet
Saveetha School of Engineering,
Saveetha Institute of Technical and
Medical Sciences Saveetha University
Chennai, Tamilnadu, India
manjulasai.sse@saveetha.com

2nd K. Krishnakumar
Department of Quantum Intelligence
Saveetha School of Engineering,
Saveetha Institute of Technical and
Medical Sciences Saveetha University
Chennai, Tamilnadu, India
krishnakumarkathiresan.sse@saveetha.com

3rd Smitha GL
Department of Quantum Intelligence
Saveetha School of Engineering,
Saveetha Institute of Technical and
Medical Sciences Saveetha University
Chennai, Tamilnadu, India
smithagl.sse@saveetha.com

4th S. Pandiaraj
Department of Quantum Intelligence
Saveetha School of Engineering Saveetha Institute of Technical and Medical Sciences Saveetha University
Chennai, Tamilnadu, India
pandiarajs.sse@saveetha.com

5th M. Prakash
Department of Quantum Intelligence
Saveetha School of Engineering Saveetha Institute of Technical and Medical Sciences Saveetha University
Chennai, Tamilnadu, India
prakashm.sse@saveetha.com

***Abstract*—The utilization of machine learning optimization methods is of utmost importance in the identification of liver tumors, attracting considerable interest in this domain. After obtaining a liver tissue sample, magnetic resonance imaging (MRI), computed tomography (CT), and ultrasonography (US) are used as imaging techniques to separate the tumor and liver. Nevertheless, the utilization of shades of gray and forms is insufficient for achieving accurate segmentation in computed abdominal CT images, mostly because of the presence of overlapping intensities and the unpredictable placements and shapes of soft tissues. The results demonstrate that our proposed technique outperforms previous state-of-the-art models in terms of overall accuracy in tumor identification. The 2D Convolutional Neural Network (CNN) model had a remarkable training accuracy of 96.47%, while the auto-encoder network closely followed with an accuracy of 95.63%. In addition, the 2D CNN network exhibited an impressive average recall rate of 95%, beating the auto-encoder network's rate of 94%. The ROC curve regions for both networks exhibited remarkable performance, with values ranging from 0.99 to 1. Out of the many machine learning approaches used, the ResUNet had the least accurate results, while the K-Nearest Neighbors (KNN) achieved the greatest accuracy rate of 86%. Conversely, the MLP demonstrated a paltry accuracy rate of about 28%. The statistical tests conducted in this study indicated a significant difference (p-value < 0.05) between the suggested approach and many existing machine learning algorithms.**

Keywords—Brain Tumor, MRI, Deep Learning, Artificial Intelligence, Transfer Learning, ResUNet

I. INTRODUCTION

The field of machine learning has shown significant growth and has attracted significant interest from both academics and professionals. It has become a prominent and significant topic of research, with enormous importance in numerous disciplines such as machine translation, speech recognition, picture recognition, and recommendation systems.

Optimization is a crucial component of machine learning. The majority of machine learning algorithms include creating an optimization model and obtaining the parameters in the objective function using the given data. The prevalence of numerical optimization methods in the era of abundant data has a substantial influence on the extensive adoption and application of machine learning models. The algorithms have a significant impact on the efficacy and efficiency of these models.

In order to promote the progress of machine learning, a collection of effective optimization strategies were suggested, leading to improved performance and efficiency of machine learning systems. Brain tumors, characterized by the aberrant and unregulated growth of cells in the brain, can be categorized into two types: benign tumors and malignant tumors. A malignant liver tumor is generally known as liver cancer. Benign tumors generally have a more slower rate of growth in contrast to malignant tumors.

The diagnosis and therapy depend on various factors, such as the kind, size, location, and stage of growth of the tumor. Research suggests that persons with brain tumors die due to incorrect diagnosis. Tumors often display heterogeneity, which poses a challenge in accurately delineating their boundaries. This hinders the precise identification necessary for prompt and efficient treatment. Detecting the Liver Tumor in its early stage allows for effective treatment and prevention of any complications.

The primary objective of this study is to examine the anatomical structure of brain slices in order to categorize them. Deep neural network optimization and reinforcement learning encounter numerous barriers and challenges. The optimization strategies discovered in many machine learning fields vary, offering useful insights for the progress of general optimization approaches.

The proposal encompasses a technique for the acquisition of brain tumor data via Medical Resonance Images (MRI). Currently, MRI is widely regarded as one of the most efficient technologies for detecting brain cancers due to its straightforwardness.

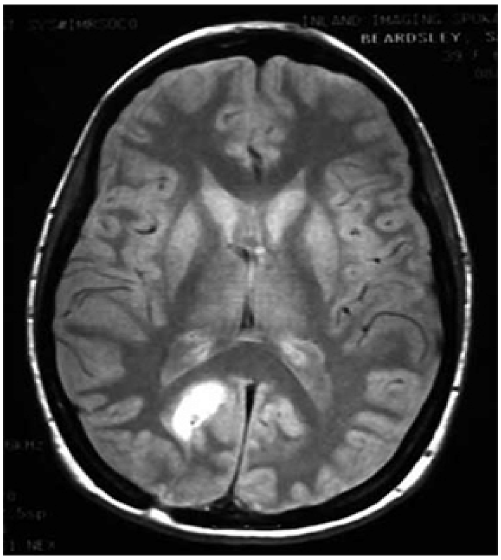

Fig. 1. Brain scans using MRI

Figure 1 exhibits brain MRI imaging slices acquired from several viewpoints, including Sagittal view, Axial View, and Coronal view. Early detection of brain tumors is a significant challenge for medical experts due to its demanding and intricate nature. The complexity stems from the diverse forms, visual attributes, dimensions, and metabolic traits of tumors, together with the existence of indistinct, noisy images. Moreover, the dispersed and intersecting characteristics of tumors, appearing elongated structures similar to tentacles, further complicate the process of diagnosis. Segmentation is an essential preprocessing procedure in the detection of brain tumors, since it improves the efficiency and accuracy of tumor identification. The early detection of brain cancers in magnetic resonance imaging (MRI) and computed tomography (CT) images requires the application of various machine learning algorithms and methodologies.

II. Related Works

In 2020, Badža and Barjaktarovic employed a Convolutional Neural Network (CNN) consisting of 22 layers to classify glioma, meningioma, and pituitary cancers. This classification was based on 3064 T1-weighted contrast-enhanced MRI scans obtained from three Chinese hospitals." The tenfold cross-validation yielded a peak accuracy of 96.56% [1].

DCNet and DCNet++ are a pair of neural networks that were developed in the year 2018." DCNet, an acronym for 'diversified capsule networks,' enhances the performance of convolutional networks by incorporating additional layers. DCNet++ utilizes a methodical learning methodology, surpassing DCNet with a success rate of 95.03% using an eightfold cross-validation on a dataset of 3064 MRI images [2].

Gumaei et al. [3] introduced an automated technique for the identification and categorization of brain tumors." Their utilization of PCA-NGIST and RELM resulted in a precision rate of 94.23% on a dataset consisting of 3064 MRI images obtained from 233 individuals. However, it is worth noting that the study did not include a comparison evaluation.

Pashaei et al. [4] utilized a Convolutional Neural Network (CNN) consisting of sixteen layers to accurately identify and diagnose pituitary, meningioma, and gliomas." The model, assessed using tenfold cross-validation on Cheng's dataset, had a notable efficacy with an accuracy rate of 93.68%, surpassing alternative machine learning techniques [4].

Abiwinanda successfully employed a Convolutional Neural Network (CNN) in 2018 to accurately identify the three most prevalent types of brain cancers." The study utilized 3064 T1-weighted CE-MRI brain tumor images from Cheng and achieved a training accuracy of 98.51% and a validation accuracy of 84.19% [5].

Paul et al. employed deep learning methodologies to classify brain images associated with meningioma, glioma, and pituitary cancers." Their research utilized Convolutional Neural Networks (CNNs) and fully connected networks on a standard dataset consisting of 3064 T1-weighted MRI images. The results showed a cross-validation accuracy of 91.43% using a five-fold validation approach [6]. dilatation [6].

III. Material and Methods

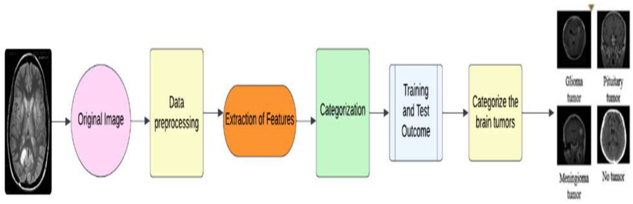

Fig. 2. Stages of the proposed methodology

The methods employed in the current investigation is depicted in Figure 2. The main stages of the current study include selecting a brain tumor dataset, preprocessing MRI images, extracting features, and classifying them using different classifiers.

A. Dataset

A dataset consisting of 3,264 MRI scans with T1-weighted contrast enhancement were utilized in this investigation [7,10]. The dataset comprised photographs categorized into four unique groups: glioma (926 photos), meningioma (937 images), pituitary gland tumor (901 images), and healthy brain (500 images). The pictures were obtained in three distinct orientations: sagittal, axial, and coronal. Figure 3 depicts several tumor shapes and their orientations on different planes, with a red line outlining the tumor region. It is crucial to acknowledge that every sufferer has their own distinct assortment of photographs.

B. Magnetic resonance imaging (MRI) picture collection

Radiologists can look at MRI pictures from a number of hospitals online. The MRI scans were stored in the database in JPEG file. The three main types of patient pictures are color, grayscale, and intensity files. When these pictures are shown, their default size is 220x220. It is possible to change color images to grayscale by using a grid with numbers between 0 and 255. This matrix has two numbers that stand for black and white: 0 and 255. Figure 3 shows the brain scans that were sent in.

Fig. 3. Provide a brain image as input.

C. *Preprocessing of Images*

The procedures for image preprocessing received grayscale brain photos after the initial MRI scan was taken. Figure 4 demonstrates the process of getting a photograph ready to be shot.

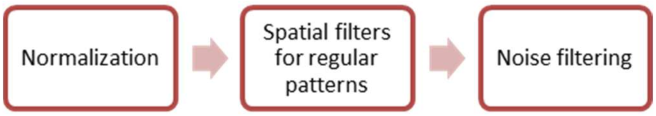

Fig. 4. Image processing procedures

D. *Normalization*

The obtained gray level images were normalized using the immerse function in MATLAB. The system utilizes an immersive feature with a resolution of 150*140 pixels and 200*250 pixels. This size provides sufficient information of the image while maintaining a minimal processing time.

E. *Noise Filtering using Spatial filters for regular patterns*

Removing noise and discovering new parameters that alter in ways that perform better for brain filtering is the objective of regular spatial pattern filters' preparation. To classify a tumor as normal (N) or aberrant (AN), the technique will pinpoint its precise location in the brain. The damaged area was next subjected to the common spatial pattern filter.

Specific aspects of the filtering process, categorized for the T_D (N) and T_H (AN) scenarios.

The auxiliary filter L was elevated to comparable characteristics as demonstrated in equations (1) and (2).

$$\frac{COV(l_{CSP}\,T_D)}{TRACE\,(T_D\,T_D^X)} + \frac{COV(l_{CSP}\,T_H)}{TRACE\,(T_H\,T_H^X)} = S \quad (1)$$

$$\frac{COV(l_{CSP}\,T_D)}{TRACE\,(T_D\,T_D^X)} = R \quad (2)$$

In this context, T symbolizes the transpose operator, S represents the identity matrix, trace (z) refers to the sum of the diagonal elements of matrix $\sum R\ of\ z$, and R designates a diagonal matrix with its elements arranged in a monotonically declining order. Based on (1) and (2), l_{CSP} was constructed and subjected to filtering. Through the use of an auxiliary filter, l_{CSP} separates the unusual traits into distinct components. There is a clear indication of a fundamental connection between T_D (N) and T_H (AN) qualities when utilizing equations (3) and (4) together.

$$T_{REF\ D} = L_{CSP}\ T_D\ (j, w) \quad (3)$$

$$T_{REF\ H} = L_{CSP}\ T_H\ (j, w) \quad (4)$$

IV. Performance Metrics

1 A true positive refers to the accurate identification of a brain tumor on an MRI scan.

2 A false positive refers to the misidentification of a brain tumor in an MRI scan that does not truly reveal a tumor.

3 A true negative refers to the accurate identification of an MRI image that does not depict the presence of a brain tumor.

4 A false negative refers to the situation where an MRI picture, which has the capacity to detect brain cancers, mistakenly classifies the image as non-tumorous.

A. *Evaluation standards*

It is critical to apply specified evaluation criteria to the model's performance in object detection after the testing and training stages are finished. The researchers employed many evaluation criteria, including F1-score, confusion matrix (CM), sensitivity (SE), specificity (SP), accuracy (AC), and precision (PR). In order to acquire these metrics, the model must be executed on 613 MRIs, and the occurrences of TP (true positive), TN (true negative), FP (false positive), and FN (false negative) cases must be documented. TP refers to accurately recognized and labeled tumor occurrences, while FP indicates instances that are incorrectly categorized as tumors when they are actually non-tumor cases. FN stands for malignancies that have not been discovered, while TN indicates correctly anticipated true negatives.

The F1-score, which is applicable to datasets with imbalanced classes, computes the harmonic mean of false negatives (FNs) and false positives (FPs). Equations (5)–(9) [8,9] are utilized to compute the accuracy, precision, sensitivity, specificity, and the F1-score for each model. These metrics jointly evaluate the overall effectiveness of the models.

$$PR = \frac{TP}{TP + FP'} \quad (5)$$

$$RE\ and\ SE = \frac{TP}{TP + FN'} \quad (6)$$

$$Specificity\ SP = \frac{TN}{TN + FP'} \quad (7)$$

The probability of the test accurately identifying a patient with the disease:

$$Accuracy\ AC = \frac{TP + TN}{TP + TN + FP + FN'} \quad (8)$$

Accuracy is a measure that indicates the proportion of misclassified samples in a dataset, providing an overall overview of the classification performance.

$$F1 - score = \frac{2(TP)}{2(TP) + FP + FN'} \quad (9)$$

TABLE I. A COMPARISON OF THE WAY THE DEEP LEARNING MODELS AND THE SUGGESTED MODEL WORK.

Models	PR (%)	RE (%)	SE (%)	SP (%)	AC (%)	F1-Score (%)
Xception	91.4	91.6	91.8	91.9	92.2	92.4
InceptionResNetV2	92.6	92.7	92.9	93.1	93.4	93.6
RNNs	93.2	93.4	93.6	93.8	94.2	94.4
InceptionV3	93.7	93.9	94.1	94.3	94.5	94.9
VGG16	94.1	94.3	94.6	94.8	95.1	95.3
Efficient Net	94.6	94.8	95.2	95.6	95.8	96.2
The proposed model (ResNet50)	96.5	96.7	96.9	97.2	97.4	97.6

Important metrics for evaluating a model's performance in healthcare settings include precision (PR), recall (RE), and F1-score. Information about the efficiency of catching potential positive occurrences, the trade-off between precision and recall measures, and the accuracy of positive predictions compared to the total number of detections may be found in these data. In deep learning, like in conventional ML, these metrics are crucial for gauging a model's efficacy and reliability.

Figure 5 displays the ResUNet model's training progress for liver segmentation over 20 iterations. Table 1 shows the results of dividing the tumor into sections and the ResUNet model's training progress after 50 iterations. It was also possible to figure out accuracy and singular value decomposition (SVD), which are two more evaluation measures. The Singular Value Decomposition (SVD) shows the difference between the imagined masks and the real masks. The suggested model was 99% correct, with an SVD score of only 0.22. Table 2 shows that this number shows the masks that were projected and those that were observed having the least amount of difference. The accuracy has gone up because of the change in how the classes are spread out. In order to process CT scans, more pixels have been put into a baseline category where tumors are very rare to show up. The accuracy measure works by adding up the TP, FP, TN, and FN scores for each class. Because of this, it favors the background class.

TABLE II. ASSESSING THE EFFICACY OF CURRENT CUTTING-EDGE MODELS AND THE SUGGESTED MODEL.

Models	PR (%)	RE (%)	SE (%)	SP (%)	AC (%)	F1-Score (%)
Xception	93.2	93.4	93.6	93.8	94.0	94.2
InceptionResNetV2	94.3	94.4	94.6	94.7	95.9	95.0
RNNs	95.2	95.24	95.28	95.4	95.6	95.8
InceptionV3	95.7	95.9	96.2	96.4	96.48	96.6
VGG16	96.1	96.3	96.5	96.54	96.7	96.9
Efficient Net	97.6	97.7	97.9	97.94	97.99	97.0
The proposed model (ResNet50)	98.5	98.7	98.8	98.86	98.9	98.91

The Xception method's accuracy of 95.6% was the lowest of all the models examined in this study when applied to the validation dataset. It was evident that all CNNs performed admirably, with only minor variations, when we examined Table 2 and contrasted the outcomes of each design utilizing the fine-tuned procedure.

In Table 2, we can see how this work's model stacks up against other models that have attempted to detect brain cancers using ML and DL techniques. Disagreements in data preparation, training, validation procedures, and computational resources make direct comparisons of research publications problematic. With a success rate of 98.5%, the suggested model in this study demonstrated exceptional accuracy.

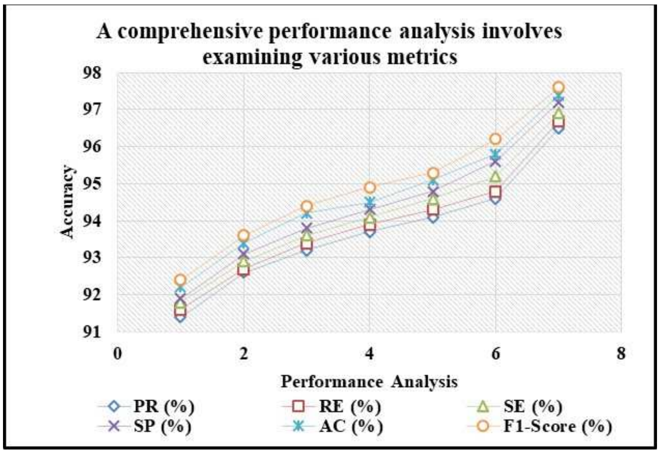

Fig. 5. Show the model's performance under different conditions,

Using a dataset of brain tumors, the researchers tested the enhanced algorithm's performance with the introduction of the Convolutional Block Attention Module (CBAM) as its attention mechanism. Several metrics were used to evaluate the model's efficacy, including F1-score, recall, specificity, sensitivity, accuracy, etc. Table 1 displays the results of these experiments, demonstrating how effective the updated algorithm is.

V. CONCLUSIONS AND FUTURE WORK

"The complexity of liver tumor cells presents a significant challenge for medical professionals in accurately predicting brain tumors." ResUNet outperforms traditional methods in terms of accuracy, training time, and memory usage due to its hybrid architecture. The main emphasis is placed on optimizing efficiency and reducing costs for users. In order to obtain faster and superior outcomes, a novel approach is utilized, leading to a training accuracy of 96.47% for the proposed Convolutional Neural Network (CNN) and 95.63% for the recommended auto-encoder network. A total of six machine-learning techniques were developed for the purpose of classifying brain tumors, in addition to the creation of two deep networks. KNN emerged as the victor with an accuracy rate of 86%, followed by SVM with 80%, and RF with 82%.

Possible future resolutions for these problems could entail investigating deep reinforcement learning (DRL), few-shot learning, and zero-shot learning. Zero-shot learning can mitigate the issue of limited training data for liver tumor classes by generating classification models for test samples that have not been encountered before. Few-shot learning allows deep learning models to acquire knowledge from a limited subset of each category in situations where there is a scarcity of annotated data. In order to decrease the system's need on precise comments and top-notch images, one can utilize deep reinforcement learning (DRL). Nevertheless, the absence of testing on real-world clinical data is a disadvantage. Despite encouraging outcomes on publically accessible information, it is imperative to validate the method using data obtained from clinical investigations. It is crucial to examine and confirm the proposed method using actual clinical data in order to ensure its usefulness, as this problem is applicable to all the models being studied.

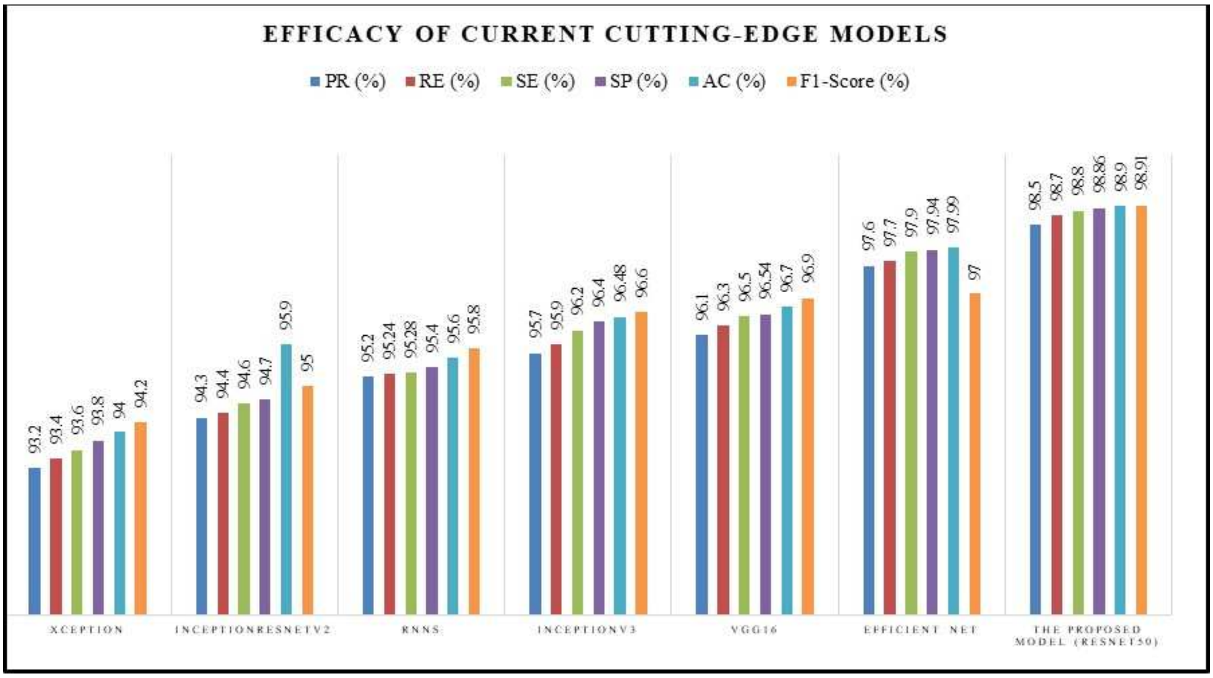

Fig. 6. Show the results of effective the current cutting-edge models

REFERENCE

[1] Badža MM, Barjaktarović MČ. Classification of brain tumors from MRI images using a convolutional neural network. Appl Sci. 2020;10(6):1999.

[2] Phaye SS, Sikka A, Dhall A, Bathula D. Dense and diverse capsule networks: making the capsules learn better. arXiv: 1805. 04001. 2018 May 10.

[3] Gumaei A, Hassan MM, Hassan MR, Alelaiwi A, Fortino G. A Hybrid feature extraction method with regularized extreme learning machine for brain tumor classification. IEEE Access. 2019;7:36266–73.

[4] Pashaei A, Sajedi H, Jazayeri N. Brain tumor classification via convolutional neural network and extreme learning machines. In: 2018 8th international conference on computer and knowledge engineering (ICCKE). IEEE; 2018 Oct 25. p. 314–9.

[5] Abiwinanda N, Hanif M, Hesaputra ST, Handayani A, Mengko TR. Brain tumor classification using convolutional neural network. In: World congress on medical physics and biomedical engineering 2018. Singapore: Springer; 2019. p. 183–9.

[6] Paul JS, Plassard AJ, Landman BA, Fabbri D. Deep learning for brain tumor classification. In: Paper presented at the Medical Imaging 2017: Biomedical Applications in Molecular, Structural, and Functional Imaging. 2017.

[7] Lee JY, Lee KS, Seo BK, Cho KR, Woo OH, Song SE, et al. Radiomic machine learning for predicting prognostic biomarkers and molecular subtypes of breast cancer using tumor heterogeneity and angiogenesis properties on MRI. Eur Radiol. 2022;32(1):650–60.

[8] Çinar, A.; Yildirim, M. Detection of tumors on brain MRI images using the hybrid convolutional neural network architecture. Med. Hypotheses 2020, 139, 109684.

[9] Sangeetha, R.; Mohanarathinam, A.; Aravindh, G.; Jayachitra, S.; Bhuvaneswari, M. Automatic detection of brain tumor using deep learning algorithms. In Proceedings of the 4th International Conference on Electronics, Communication and Aerospace Technology (ICECA 2020), Coimbatore, India, 5–7 November 2020; pp. 1–4.

[10] Waqas,M.; Tu, S.; Halim, Z.; Rehman, S.U.; Abbas, G.; Abbas, Z.H. The role of artificial intelligence and machine learning in wireless networks security: Principle, practice and challenges. Artif. Intell. Rev. 2022.