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A Secure IoT-Enabled Machine Learning Framework for Brain Tumor Classification and Prediction Using MR Image Data

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Abstract—Brain tumor identification and classification have improved due to the quick development of medical imaging and machine learning technology. This paper presents two approaches to secure image transmission in the Internet of Things (IoT): a comprehensive approach for brain tumor prediction and classification using a strong IoT infrastructure with cutting-edge machine learning models and a security approach with the implementation of the AES-ECC hybrid model in the MQTT communication protocol for image data encryption and decryption. We make use of a heterogeneous dataset that we sourced from the Kaggle Dataset platform, which includes four different types of MRI scans of brain tumors from 2870 patients. Our proposed methodology starts with the safe acquisition and transfer of MRI images through an IoT protocol infrastructure to a cloud-based platform. CNN, DenseNet, ResNet and G-Net are some of the sophisticated machine learning models that are used to interpret and analyse these pictures. The computer is trained to identify photos of brain tumors into the appropriate groups using all above four models. According to the data, our suggested CNN model performs better than the others, obtaining an amazing 89% accuracy rate. Nonetheless, we want to achieve even greater improvement in forecast precision by utilising ensemble boosting methodologies. Boosting the CNN model with Ada-Boost, Gradient Boost, XG Boost and Cat Boost algorithms aims to maximize prediction performance. We find that the CNN algorithm combined with XG Boost outperforms all other ensemble methods with an amazing accuracy rate of 97%. This encouraging result highlights how combining cutting-edge machine learning algorithms with IoT infrastructure can lead to better brain tumor classification and prognosis. The creation of more precise and effective diagnostic instruments for the identification of brain tumors is one of our study's many implications, one that will ultimately improve patient outcomes and the healthcare industry.

Keywords-IoT, AES, ECC, ML, MRI, Voting Model, Boosting Model

I. INTRODUCTION

The emergence of the Internet of Things (IoT) has created new opportunities for the healthcare industry by providing creative solutions to the pressing problem of brain tumor prediction and categorization. Because of their intricacy and potentially serious implications, brain tumors require early and precise detection. This picture is set to change as a result of the integration of advanced machine learning models with IoT infrastructure[18-20]. The integration will provide simplified data collecting, secure transfer and improved diagnostic capabilities.

Machine learning is one of the key hidden insights techniques in the Internet of Things[1]. As seen in figure 1, this mix of technologies functions differently for every decision making process in the fields of business, security systems, education departments and other healthcare systems. The Internet of Things can now characterize hidden patterns in vast amounts of data thanks to machine learning, which is used to forecast and suggest patterns to the systems. A kind of artificial intelligence called machine learning (ML) enables computers to learn from their past mistakes and advance without the need for human programming. Robots can behave in ways that are quite similar to humans thanks to machine learning.

Enormous volumes of data can be mined for the essential information by using algorithms that machine learning can create based on associations and trends in the data[21]. Automated devices that generate patient files and continuously monitor patients have been created in the healthcare industry through the use of IoT and machine learning. In the healthcare sector, managing IoT data requires knowledge of several machine learning techniques. Machine learning may have applications in game play, bioinformatics, healthcare, marketing, intrusion detection, education sector[22] and other fields. It enables robots and computers to make decisions based on data rather than having them specifically programmed to carry out a given task. These algorithms or programs are meant to learn and get better over time when they are exposed to new or unidentified data. Because there is so much data available, the value of machine learning is evident across many facets of society. A thorough demonstration of the healthcare applications has been provided.

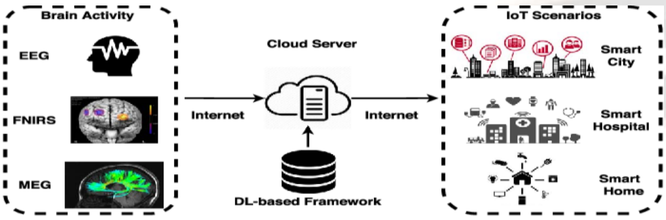

Figure-1: IoT as a Brain and Computer Interface

This work uses state-of-the-art machine learning models such as CNN, DenseNet, ResNet and G-Net along with IoT technologies to conduct a thorough research of brain cancer classification and prediction. The Kaggle Dataset contains an abundance of MRI data from 2870 patients with four different forms of brain tumors, providing a large and varied dataset for model training and validation.

Making sure that MRI pictures are securely transmitted from IoT sensors to cloud-based platforms—where the data will be analyzed—is one of our main goals. To protect the confidentiality and integrity of patient data while it is being transmitted, security is essential. In order to solve this, we use MQTT (Message Queuing Telemetry Transport), an Internet of Things communication protocol that is ideal for guaranteeing the safe transfer of MRI data to cloud storage[2]. The procedure includes converting the image to binary format, creating frames and encrypting the data using cutting-edge security methods like ECC (Elliptic Curve Cryptography) and AES (Advanced Encryption Standard). Specifically, a novel hybrid technique is developed to maximise energy economy and key generation time by combining AES and ECC.

Our study is centered around two main goals. The initial goal is to build a strong IoT security architecture, with a particular focus on optimizing and choosing security algorithms. We do a thorough simulation to assess the effectiveness of several encryption techniques and we find that the hybrid AES-ECC model performs best in terms of security and efficiency.

This study's second task involves comparing machine learning models in order to determine which model is the most effective and precise for classifying and predicting brain tumors. This evaluation takes into account a number of factors, such as loss, validation loss, accuracy and validation accuracy. Our results clearly indicate that the CNN + XG Boost combination is the most accurate and successful model, with an exceptional accuracy rate of 97%.

To summaries, our study focuses on two critical facts of brain tumor classification and prediction: first, building a safe Internet of Things infrastructure for data transfer and second, choosing the best machine learning model to improve diagnostic precision. This work represents a major advancement in medical technology, offering more accurate and safe methods for the detection and management of brain tumors.

II. Related Work

In their research, Abdulbaqi H S et al.[3] have proposed a hybrid method that uses an HMRF-EM algorithm to produce final labels and makes it easier to diagnose brain tumors from brain MRI images. The outcome of the HMRF-EM algorithm has been subjected to threshold application. As a final outcome of the entire procedure, the result obtained displays a high degree of accuracy in the segmentation of MRI brain tumor images, which opens up the possibility of estimating the tumor's future size.

A methodology for classifying brain tumours was presented by Kang J. et al. [4]. It involved the use of machine learning (ML) classifiers in conjunction with an ensemble of deep features that were obtained from pre-trained convolutional neural networks (CNNs). To extract deep features from brain magnetic resonance imaging (MRI), they proposed a framework and used different pre-trained CNNs. A number of machine learning classifiers then evaluated the extracted deep features. The three best deep features as determined by different machine learning classifiers were selected and integrated to form an ensemble that could forecast the result. Three datasets (BT-small-2c, BT-large-2c and BT-large-4c) were used in their experimental setup to thoroughly assess brain tumour classification using nine different ML classifiers and thirteen different pre-trained CNNs. According to the experimental findings, applying the suggested architecture produced the following recommendations: (1) DenseNet-169 deep feature by itself is useful for small MRI datasets that contain only two classes (tumour, normal); (2) an ensemble of DenseNet-169, Inception V3 and ResNeXt-50 deep features is recommended for large MRI datasets that contain two classes (tumour and normal); and (3) combining DenseNet-169, ShuffleNet V2 and MnasNet deep features is a good choice for large MRI datasets that contain four classes (tumour, glioma, meningioma and pituitary). Importantly, the authors addressed the shortcomings of individual CNN models by introducing a novel feature ensemble technique that showed better and more dependable results, especially for large datasets. The results imply that the suggested approach, which combines ML classifiers with an ensemble of deep features, is useful and efficient for classifying brain tumours.

Using brain MRI data, Muhammad Aamir et al.[5] proposed a straightforward and accurate method for classifying brain tumors, such as meningiomas, gliomas and pituitaries. To improve image quality, non-linear techniques and optimal contrast are applied. Tumor locations are ascertained by means of segmentation and clustering. With the corresponding input image, these scored locations are fed to EfficientNet-B0 for feature extraction. These locations are further optimised to enhance detection performance. To determine the tumor category and location, these locations are then aligned and examined. The accuracy of classification was increased by moving features from detection layers to classification layers. Furthermore, data augmentation methods were used to prevent overfitting of the network. The free FigShare dataset was used to evaluate the suggested model. In contrast to other methods of the same kind, the experiments yielded reliable findings. Overall, the classification accuracy of their suggested method was 95.98%. Our model achieved higher sensitivity (97.31%, 97.83% and 99.46%), specificity (98.59%, 99.51% and 99.34%) and accuracy (98.31%, 98.72% and 99.46%) for the Meningioma, Glioma and Pituitary classes. Thus, it seems that their suggested model works well for categorising brain tumors.

Using non-linear strategies and optimal contrast, a model developed by Yurong Guan et al. [6] will first enhance the visual quality of the image. The second method is to locate the tumours using segmentation and clustering techniques. These locations are scored and the corresponding input image is sent to EfficientNet for feature extraction. Thirdly, these locations undergo additional refinement to enhance detection performance. Following alignment and processing, these locations are used to determine the tumor's categories and location. The classification accuracy has increased by shifting features from detection layers to classification layers. Their proposed method has a 98.04% overall classification accuracy.

A study conducted by Swain S. P. et al. [7] involving 25,000 patients with heart disease compared the Neural Basis Model (NBM), Random Forest (RF), Logistic Model Tree (LMT) and Decision Tree (DT) to estimate the probability that a patient may have a stroke. After examining the different models, they discovered that the Decision Tree (DT) functions the best. To help in the accurate diagnosis of heart diseases, they have proposed a new model for disease prediction.

A proposal regarding the segmentation of the tumor region in MRI brain images was made by Harshavardhan A et al. [8]. In order to obtain detailed diagnosis results, their suggested method's segmentation accuracy and execution time must be verified through the application of feature extraction and classification phases.

A novel algorithm was presented by M. Kadkhodaei et al.[9] for the segmentation of tumors in MR images. This algorithm used saliency detection in addition to 3D super-voxels for segmentation. Based on their intensities, the super-voxel algorithm separated improved MR images into informative clusters. Tumor regions in the original images were highlighted with the help of saliency detection. Following the extraction of features from the saliency map and super-voxels, each super-voxel was categorised into background classes or tumor cores. The neural network was used to classify these data. Finally, the classification output based on the saliency map was refined by the weighted median filter. They used the BraTS 2012 dataset to test their method and in terms of Dice score, their results were superior to those of a more recent compatible method.

Anwar S. M. et al.[10] make it very evident that the EMAP algorithm and k-means clustering are used to perform automatic brain tumor segmentation on the BRATS dataset. When compared to earlier methods, the suggested technique's accuracy and computation time are good. The MICCAI challenge's ground truth is used to assess the accuracy. The DICE coefficient illustrates the 92% segmentation accuracy attained by the suggested method. The benefit of the suggested method is that it can be used to segment entire tumors as well as subtumor regions and it doesn't require any training.

According to Wulandari A. et al.'s experimental findings [11], the skull shell should be removed prior to segmenting the brain tumor because its colour is similar to that of the tumor itself. By initialising two lines, the Watershed Segmentation method is used to cut the skull. When brain tumors are segmented using the thresholding method. Subsequent to the threholding of results, the largest contour search was conducted in order to distinguish the tumor object from surrounding tissues. Based on the results of the system test, the tumor area calculation has an average error of 10%.

YOLO v5 and FastAi, two distinct deep learning-based methods for brain tumor identification and categorization, have been proposed by Nadim Mahmud Dipu et al. [12]. The development of an automated real-time brain tumor detection system will be greatly aided by these models. A system like this will significantly increase the precision and efficacy of brain tumor and cancer diagnosis. Additionally, it will significantly enhance the healthcare system's capabilities. Our YOLOv5-based detection model achieved an accuracy of 85.95%, while the proposed CNN-based classification model achieved an accuracy of 95.78%.

A technique that allows for the implicit segmentation of brain images containing tumors through atlas-based registration has been proposed by Stefan Bauer et al. [13]. Not only is this crucial for brain tissue segmentation, but it also makes it simple to identify sub-cortical structures through label map propagation, which is helpful when planning radiotherapy or surgery to remove brain tumors.

A method utilising multiple wavelet levels has been proposed by Mircea Gurbin et al. [14]. CWT is used to obtain the high accuracy portion of the method. In segmentation, the CWT keeps edges from being lost. The outcome demonstrates that SVMs with the right training data sets can accurately identify benign, malignant and healthy brain tumors by differentiating between abnormal and normal tumor regions. SVMs have major computational advantages in practise. The doctor needs to know this classification in order to make an accurate diagnosis and suggest the best course of action. The results obtained indicate that when compared to DWT, CWT offers higher computation. It is preferable to utilise CWT, even if it requires more computation time. They advise using a hybrid strategy to effectively address the issues with brain tumor detection and classification.

Somaya A. El-Feshawy et al. [15] carried out a singular study on various methods of brain tumour detection. They used a CNN-based deep learning model to detect tumours in two different scenarios. One may think of this model, also known as OMRES, as an altered version of the ResNet18 network. In the first case, the suggested model receives the brain image straight. In the second case, brain tumours can be detected early thanks to an Internet of Things (IoT)-based framework. This entails using a multiuser detection system and uploading images to the cloud so that anyone, anywhere can accurately classify brain tumours using the system. Three optimisation algorithms were also covered in the study. Furthermore, using metrics like recall, F1-score, the confusion

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matrix, ROC curve, accuracy, precision and specificity, the proposed model was contrasted with other pre-trained models. According to the simulation results, the RMSProp algorithm yielded the best results when compared to other algorithms, with a dropout rate of 0.5. The suggested model performed better in the first scenario than traditional CNNs, attaining an accuracy of 98.67% and a maximum sensitivity of 100%. It showed a sensitivity of 94.2% and an accuracy of 95.53% in the second scenario. All things considered, these results highlight how well the suggested model recognises and classifies MRI brain images.

Cuneyt Ozdemir [16] presented a CNN architecture that produced a 98.69% classification accuracy for brain tumors. The suggested model is quick and easy to use. The model performance was found to be significantly improved by assigning high kernel sizes and strides values to the first layers of the convolutional layers, low values to the middle layers and small strides values to the pooling layer. The suggested CNN architecture was contrasted with research that used the same dataset and published transfer learning models. These comparisons led to the recommend model producing high-scoring outcomes. Among standalone models, the model's classification success is state-of-the-art.

Together, the reviewed papers above offer a thorough understanding of the current state of brain tumor detection, classification and segmentation. The methods range from state-of-the-art deep learning models and IoT-based frameworks to conventional algorithms. The aim of these studies is to improve the efficiency and accuracy of brain tumor diagnosis and the findings show promise in this regard. Interestingly, a large number of the papers stress the significance of dataset size and the necessity of customised models for various forms of brain tumors. A major advancement in the field, the integration of machine learning, advanced imaging techniques and security protocols in IoT communication holds the promise of more accurate and effective brain tumor diagnosis and classification.

The combined results of these varied research projects add to the expanding corpus of information regarding medical imaging and brain tumor diagnosis. Brain tumor detection and classification accuracy is being improved through the use of cutting edge technologies like deep learning, wavelet transformations and Internet of Things (IoT) systems. Beyond the realm of medical research, these studies have broad implications because improved diagnostic tools can have a substantial positive impact on the healthcare sector, ultimately leading to better patient outcomes and laying the groundwork for future advancements in the field.

In this work, we have done new contributions to the understanding of the security of Internet of Things (IoT) communication in medical imaging, the assessment and selection of machine learning models for the classification of brain tumors and the application of ensemble methods to optimise predictive performance. When taken as a whole, these contributions improve the diagnostic and classification state-of-the-art for brain tumors and provide insightful advice to practitioners and researchers.

III. Research Design

We gathered a dataset for this study from the Kaggle database. 2870 MR images of three distinct kinds of brain tumors as well as some non-tumor images are included in our data set. Of the total data, we use 70% for machine learning training using various machine learning voting models, such as CNN, DenseNet, ResNet and G-Net; the remaining 20% are used for testing and the remaining 10% are used for validation tasks. We can determine the accuracy levels for categorising brain tumors with the use of these models. AES-ECC hybrid, a security algorithm that we also proposed in this research, aids in the safe transfer of data from sources to destinations. Finally, in order to improve the accuracy of the suggested voting model, we employed an ensemble boosting model. The flowchart figure 2 below illustrates the specific workflow of our work.

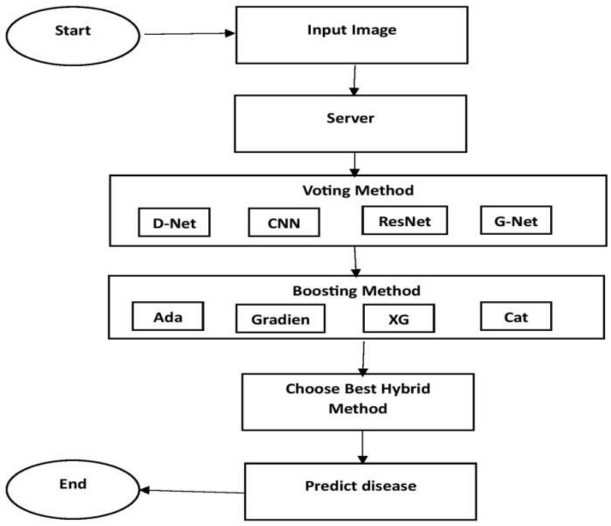

Figure 2: Flow Chart of our Proposed Work

IV. Proposed Methods

Medical research indicates that there are several different kinds of brain tumors. For a patient to receive appropriate treatment and make a full recovery, early detection and accurate type identification of a brain tumor are essential. For the purpose of training and testing machine learning models, we have included MR images of three different types of brain tumors in this study: meningioma, pituitary and glioma tumors. Two challenges have been identified based on our research. The first difficulty arises when we use IoT sensors to gather test MR images from patients and then use IoT communication frameworks and the MQTT protocol to transfer the data to the cloud. The second is to use existing machine learning models to accurately classify and predict the type of tumor.

Here, we have obtained a dataset from the Kaggle database that includes 2870 MR images of three distinct types of brain tumors: meningioma tumors, pituitary tumors and glioma tumors, along with a few non-tumor MR images, as illustrated in figure 3. The data were split up into five different subgroups.

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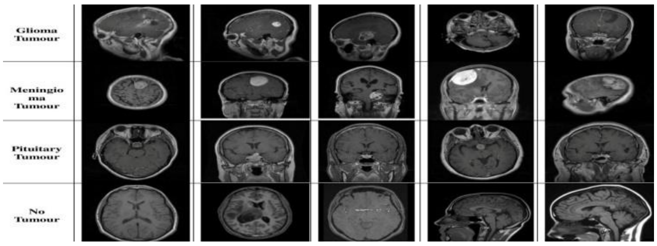


Figure 3: Data Set of Different Types of Brain Tumors

The machine was then trained using four popular machine learning voting models. DenseNet, CNN, ResNet and G-Net are these models. Following the completion of the training, we took some sample test images and conducted test activities. Of the 2870 total images, we have utilized 70% for training, 20% for testing and 10% for validation purposes. According to our research, CNN outperforms the other three models, as seen in figure 4.

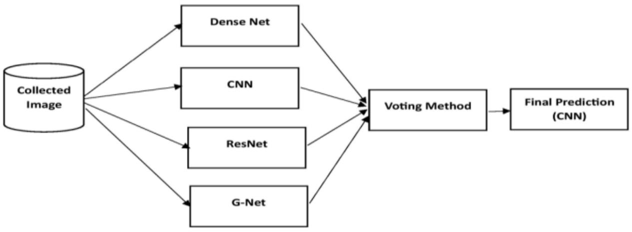


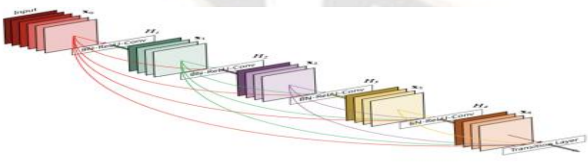
Figure 4: Voting or ML Models Implementation

A. ML Voting Models

There are various types of machine learning voting models. Out of these some common models are as bellow:

1. DenseNet

DenseNet is a type of specialised convolutional neural network that uses dense connections between its layers. Dense Blocks serve as the intermediaries for these connections, directly connecting any two layers that have matching feature-map sizes. This structure maintains feed-forwardness by allowing each layer, as shown in figure 5, to receive additional inputs from all previous layers. It then sends its own feature maps to every layer that comes after.



$$a^{[l]} = g([a^{[0]}, a^{[1]}, a^{[2]}, \dots \dots \dots \dots, a^{[l-1]})$$

Figure 5: Work Flow Structure of DenseNet

Convolutional neural networks that use dense connections between layers are known as DenseNets. All layers are directly linked together (as long as their feature-map sizes match) by Dense Blocks, which facilitate these connections.

2. CNN

The most common application of convolutional neural networks (CNN/ConvNet), a class of deep neural networks in deep learning, is the analysis of visual imagery. These days, when we think of a neural network, we think of matrix multiplications; however, ConvNet functions differently. It employs a special technique called convolution. Figure 6 illustrates how convolution works mathematically. It takes two functions and produces a third function that describes how the two functions' shapes interact.

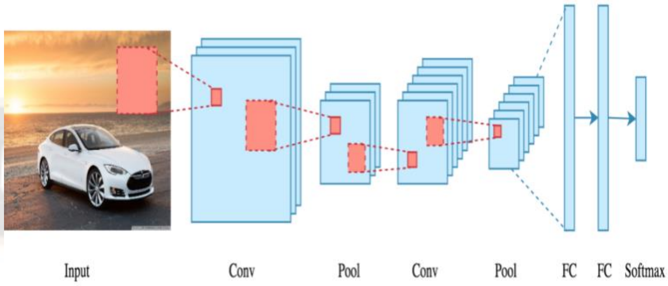


Figure 6: Work Flow Structure of CNN

3. ResNet

A particular kind of neural network architecture known as ResNet (short for Residual Network) was unveiled in 2015. It was created to address the issue of deep neural networks' vanishing gradients, which was impeding their effectiveness on demanding image recognition tasks.

4. G-Net

G-computation, a causal inference technique for calculating the effects of general dynamic treatment strategies, is the foundation of G-Net. The majority of previous g-computation implementations were constructed with classical regression models. Rather, G-Net uses a recurrent neural network architecture to extract intricate temporal and nonlinear relationships from the data.

With the help of the four machine learning models mentioned above, we have trained machines on 70% of the dataset. Next, 20% of the image data is selected for testing. To begin with, we must choose an MR image for testing. Next, as indicated in figure 7, we must convert it to binary image format. We were able to gather binary data from that binary image and create a frame for transmission. Prior to the frame being transmitted, it must be encoded using the proper security algorithm.

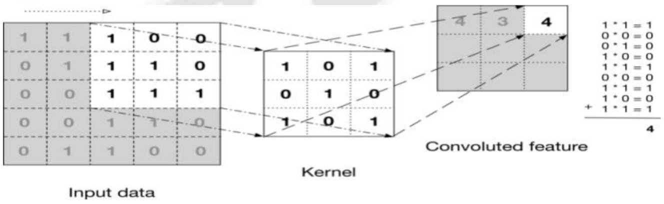


Figure 7: Method of Converting Image Data to Binary Format Data

Here, we offer an IoT protocol security framework that enables us to gather patient data and transfer it to the cloud while adhering to strict security guidelines. We focused our attention on safely gathering and transmitting the magnetic resonance image through an IoT environment's wi-fi network, even though medical diagnosis data is vital for a patient's survival. The collected data can be securely transmitted from source to destination with high security measures thanks to a variety of IoT communication protocols. Therefore, emphasis should be placed on proposing an appropriate security algorithm that will aid in more energy efficient, faster and secure transmission. According to many research, MQTT is a commonly used IoT communication protocol in IoMT. In this study, we simulated the Python codes for the AES, ECC and AES-ECC hybrid methods. The results show that the AES-ECC hybrid method's key generation time is significantly faster than that of the AES and ECC algorithms. By taking a screen grab of the simulation results, Figure 8 compares three different algorithms.

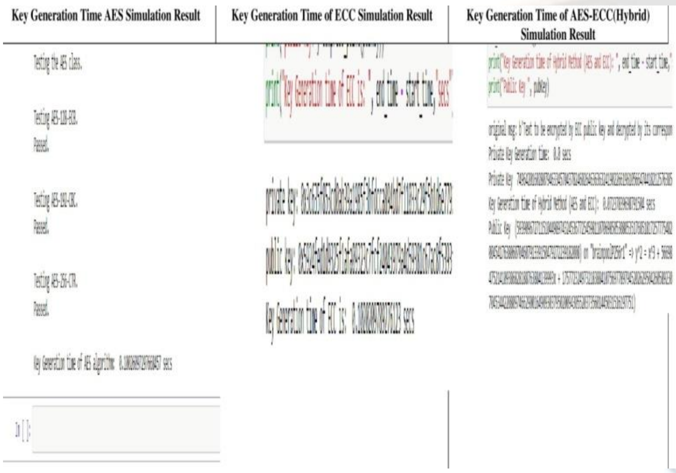


Figure 8: Python Simulation Result of AES, ECC, AES-ECC Algorithms for Key Generation Time

It is a well-known fact that an AES-ECC hybrid algorithm will use less energy to complete a task if key generation takes less time. In order to provide secure data communication, we have presented the AES-ECC algorithm for the MQTT protocol in this research.

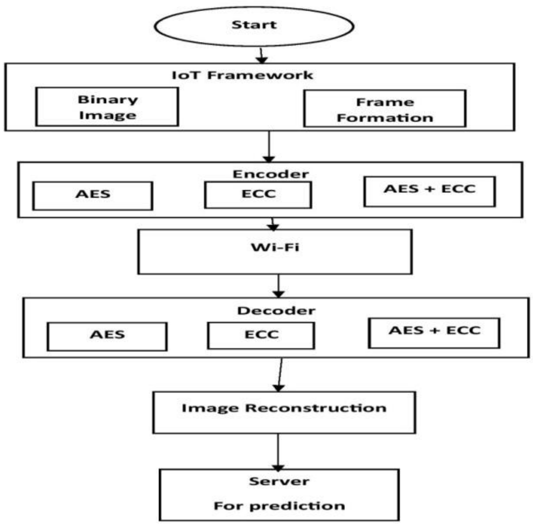


Figure 9: Process for MR Image Data Encryption, Transmission and Decryption in IoT Environment

Then we have used the data frame and key of AES-ECC algorithm for encoding the data and transmit that data through the Wi-Fi medium. Also decoding process has performed for image reconstruction by using same key. Figure 9 shows detail description of our image encryption and decryption methodology. Figure 10 showing the performance of our proposed algorithm i.e. AES-ECC with a comparison to AES and ECC algorithm.

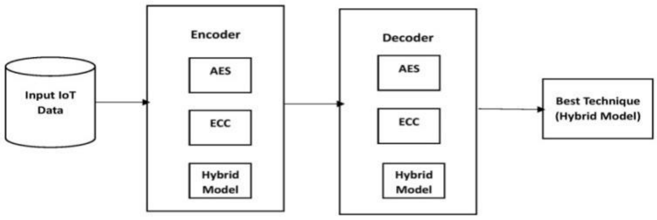


Figure 10: Process for MR Image Data Communication through IoT Communication Environment

Above four machines learning models such as CNN, DenseNet, ResNet and G-Net are used for training and testing purposes. After the training and testing work, we have collected different parameter values like Accuracy, Val-Accuracy, Loss and Val-Loss of the above models for comparison work. The results indicate that CNN outperforms the best than other models, achieving an impressive accuracy rate of 89%. However, we seek further enhancement in predictive accuracy by employing ensemble boosting techniques. Ada Boost, Gradient Boost, XG Boost and Cat Boost algorithms are applied to the CNN model with the aim of maximizing predictive performance. Remarkably, our findings reveal that the XG Boost algorithm surpasses all other ensemble methods as shown in figure 11, yielding an outstanding accuracy rate of 97%. So here we are proposing CNN with XG Boost is the best model for finding accuracy percentage to classify brain tumor very quickly and trustworthy result.

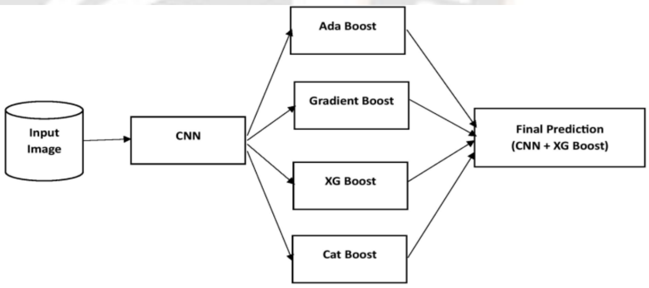


Figure 11: Work Flow Structure for Implementing Boosting Models

B. ML Boosting Models

In machine learning, boosting is a technique used to lower errors in the analysis of predictive data. With labelled data, data scientists train machine learning models—a type of software—to make predictions about unlabeled data. The accuracy of the training dataset determines how many predictions a single machine learning model makes. For instance, a model designed to identify cats might mistakenly identify a black cat if it has only been trained on pictures of white cats. By training several models consecutively, the boosting model attempts to get around this problem and raises the system's accuracy as a whole.

1. AdaBoost Model

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An ensemble machine learning algorithm called AdaBoost is useful for many different types of regression and classification problems. This supervised learning algorithm creates a strong learner by merging several weak or base learners (like decision trees) to classify data. In order for AdaBoost to function, the training dataset's instances are weighted according to how well prior classifications worked.

2. Gradient-Boost Model

Each new model created using gradient descent is trained to minimise the loss function, which could be the previous model's cross-entropy or mean squared error. Gradient boosting is an extremely powerful boosting algorithm that can make several weak learners become strong learners. The algorithm determines the gradient of the loss function in relation to the predictions made by the current ensemble at each iteration. The next step is to train a new weak model to minimise this gradient. The predictions from the new model are then added to the ensemble and this process is repeated iteratively until a predefined stopping condition is met.

3. XG-Boost Model

XGBoost is a distributed gradient boosting library that has been optimised for scalability and efficiency in the training of machine learning models. By combining the predictions of multiple weak models, this ensemble learning technique produces a stronger prediction. The machine learning algorithm known as Extreme Gradient Boosting, or XGBoost, has become well-liked and widely used due to its ability to manage sizable datasets and attain cutting-edge results in numerous machine learning applications, such as regression and classification.

4. Cat-Boost Model

We can use CatBoost, an open-source, high-performance gradient boosting library on decision trees, for tasks related to ranking, regression and classification. CatBoost achieves high performance on large and complex data sets with categorical features by combining gradient-based optimisation, ordered boosting and random permutations.

V. RESULT ANALYSIS

In this research, we have worked on two areas. First have proposed a good performance security algorithm i.e. AES-ECC Hybrid Algorithm for data communication by making a comparison with other two algorithm AES and ECC. Here we have performed code simulation of above three algorithms by using python and we got the results as bellow table that our purposed model is achieving good results pointing to performance of MQTT protocol of IoT. Table 1 shows the time which is consumed for key generation by three algorithms: AES, ECC and AES-ECC Hybrid model at implementation time.

Table 1: Times Consumes for Key Generation

Algorithm	Time
AES	0.100
ECC	0.102
AES-ECC Hybrid	0.072

In figure 12 representing the comparison the key generation time of AES, ECC and AES-ECC Hybrid model with a clear indication that AES-ECC hybrid model will take less time for key generation. Less time in key generation also results more benefits like: quick encryption, quick message passing, quick decryption and most important thing is less energy consumption. So our proposed security algorithm AES-ECC Hybrid model is best suitable for IoT protocols like MQTT and CoAP.

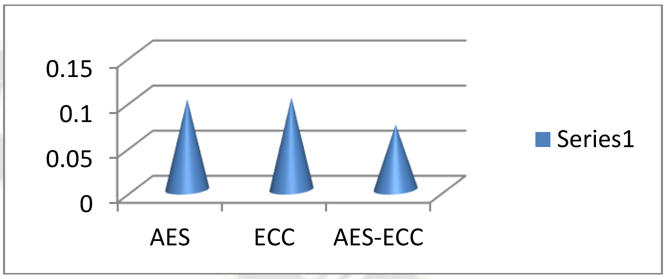

Figure 12: Performance Analysis of AES, ECC and AES-ECC based on Their Key Generation Time

In second, the dataset collected and divided into five different sample sets. Each set of data are used to train the machine by four different ML models i.e. CNN, DenseNet, ResNet and G-Net separately. Once the models are trained, they are tested with the remaining 20% of values of dataset. The predicted dataset are compared with the actual dataset. The parameters loss, val-loss, accuracy and val-accuracy are calculated for four different models and the error parameters are represented below in tabular format as well as pictorial format. Based on the overall comparisons we have confirmed that CNN is giving best result as compared to other three models as mentioned above.

Bellow table-2 and its graphical representation figure-13 presenting the accuracy levels received by four selected machine learning models, which clearly indicating that CNN achieved impressive results than other three mentioned models.

Table 2: Comparison of DenseNet, CNN, ResNet, C-Net Models on the Basis of Accuracy Values

Accuracy	Dense Net	CNN	ResNet	G-NET
Dataset-1	59	88	65	61
Dataset-2	58	88	64	61
Dataset-3	58	89	65	61
Dataset-4	59	88	65	61
Dataset-5	59	89	64	61

LOSS	Dense Net	CNN	ResNet	G-NET
Dataset-1	0.25	0.26	0.28	0.23
Dataset-2	0.41	0.21	0.41	0.2
Dataset-3	0.19	0.73	0.19	0.65
Dataset-4	0.55	0.8	0.54	0.15
Dataset-5	0.12	0.44	0.11	0.29

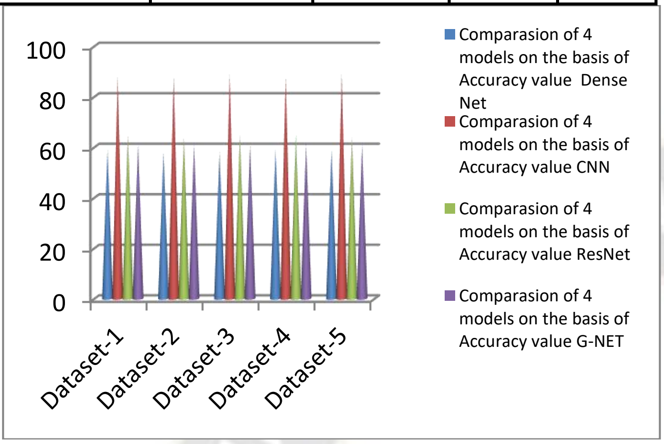

Figure 13: Graphical Representation of DenseNet, CNN, ResNet, C-Net Models on the Basis of Accuracy Values

Bellow table-3 and its graphical representation figure-14

Val-Accuracy	Dense Net	CNN	ResNet	G-NET
Dataset-1	62	91	68	63
Dataset-2	61	91	67	63
Dataset-3	61	92	68	63
Dataset-4	62	91	68	63
Dataset-5	62	92	68	63

presenting the val-accuracy levels received by four selected machine learning models, which clearly indicating that CNN also achieved impressive results.

Table 3: Comparison of DenseNet, CNN, ResNet, C-Net Models on the Basis of Val-Accuracy Values

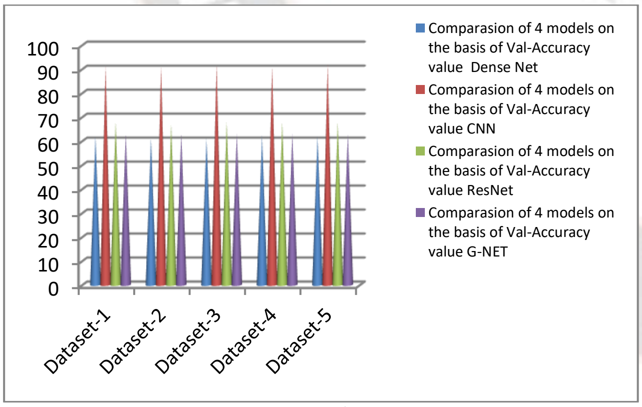

Figure 14: Graphical Representation of DenseNet, CNN, ResNet, C-Net Models on the Basis of Val-Accuracy Values

Bellow table 4 and its graphical representation figure-15 presenting the loss values received by four selected machine learning models, which clearly indicating that CNN achieved impressive results with average percentage loss than other three mentioned models.

Table 4: Comparison of DenseNet, CNN, ResNet, C-Net Models on the Basis of Loss Values

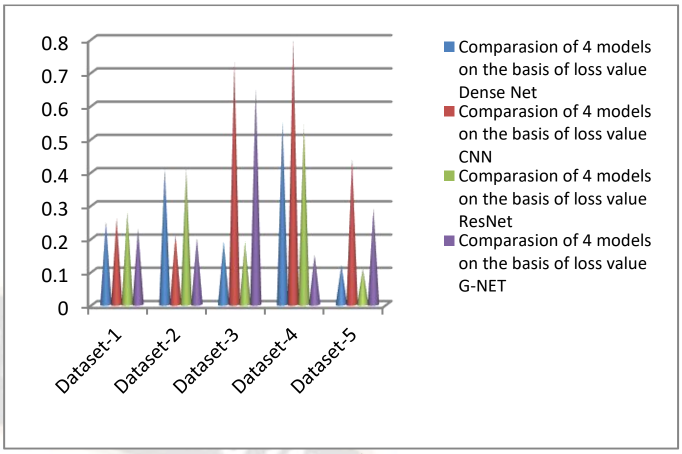

Figure 15: Graphical Representation of DenseNet, CNN, ResNet, C-Net Models on the Basis of Loss Values

Bellow table-5 and its graphical representation figure-16 representing the val-loss values received by four selected machine learning models, which clearly indicating that CNN achieved impressive results with average percentage of val-loss values than other three mentioned models.

Table 5: Comparison of DenseNet, CNN, ResNet, C-Net Models on the Basis of Val-Loss Values

VAL-LOSS	Dense Net	CNN	ResNet	G-NET
Dataset-1	0.38	0.12	0.41	0.16
Dataset-2	0.35	0.39	0.34	0.55
Dataset-3	0.12	0.89	0.12	0.25
Dataset-4	0.31	0.73	0.3	0.44
Dataset-5	0.63	0.34	0.61	0.16

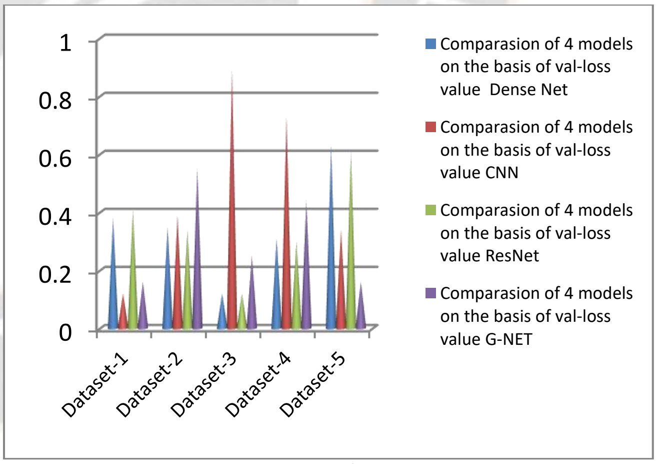

Figure 16: Graphical Representation of DenseNet, CNN, ResNet, C-Net Models on the Basis of Val-Loss Values

Table-6 and its graphical representation figure-17 representing the values received from different boosting models which are imposed on our proposed CNN model and figure-17 representing its corresponding graphical representation.

Table 6: Values Received from Boosting Models Implemented on CNN

Ensemble ML Model

Model Name	Accuracy in Percentage
Adaboost	91
Gradient Boost	93
XGBoost	97
Cat Boost	86

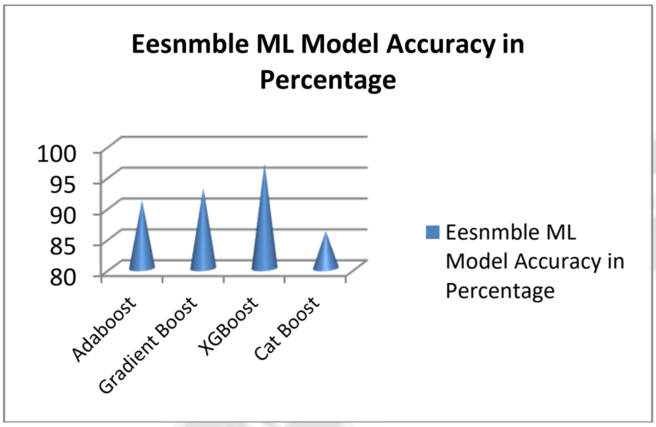

Figure 17: Representation of Boosting Models Performance on CNN

VI. CONCLUSION

This work constitutes a major advance in the field of brain tumor classification and prediction. The study focuses on two main areas: creating a strong security algorithm for Internet of Things (IoT) communication and applying machine learning models to precisely classify brain tumors. The AES-ECC hybrid algorithm was presented by the authors as an effective and safe data encryption technique for use with the MQTT Internet of Things communication protocol in the first section of the study. Simulations comparing the AES and ECC algorithms show that the hybrid AES-ECC approach performs better than alternatives, guaranteeing quick and energy-efficient transmission of MRI image data. In order to predict and categorise various kinds of brain tumors, machine learning models such as CNN, DenseNet, ResNet and G-Net were applied in the second phase of the study. Notably, the CNN model outperformed the other models (DenseNet: 59%, ResNet: 65%, G-Net: 61%), coming in at an astounding accuracy rate of 89%. Ensemble boosting techniques, utilising the AdaBoost, Gradient Boost, XG Boost and Cat Boost algorithms, were utilised to augment the predictive performance. The combination of CNN and XG Boost produced the best accuracy rate of all, at 97%, indicating a significant increase in classification accuracy.

To summarise, this study highlights the importance of the CNN model as the best method for classifying and predicting various types of brain tumors, particularly when combined with XG Boost. This research makes use of a wide range of datasets and security algorithm advancements to present a viable route towards brain tumor diagnosis and classification that is more precise and effective, with significant consequences for patient outcomes and healthcare.

CONFLICTS OF INTEREST

The authors declare that they have no conflict of interest.

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