Image and Signal Classification with Machine Learning and Deep Learning Algorithms.

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Abstract—**The classification of signal and image is one of the most buzzing topics in the field of machine learning and Artificial Intelligence. In our everyday life, we need to classify different signals and images for different purposes. Specially in medical science, doctors predict anomalies by analyzing diagnostic reports. Some of them are images like X-rays, MRI, Ultrasonic graphs and some of them are signals such as PCG, ECG, EEG and so on. In this paper, we will be analyzing specifically machine learning methods that have been developed to classify images and signals. For image classification, we have worked on a dataset to predict food images and their classes. We used transfer learning approach where five different pre-trained CNN models are implemented on the dataset along with a CNN model that is built from scratch and trained and tested on the dataset. The best pre-trained model we have found is VGG19 with an accuracy of 94% and for the scratch CNN model, the accuracy is found 78%. We compared the result of our customized CNN model with those five pre-trained models. For signal classification, EEG signal is used to classify epileptic seizure disease from a publicly available dataset. CNN is also used this time to predict epilepsy and from the CNN model, we got an accuracy of 98%.**

Index Terms—**Convolutional Neural Network, Food Image Classification, Transfer Learning, Tensorflow, Keras, Electroencephalogram (EEG), Epileptic Seizure.**

I. Introduction

In the age of the fourth industrial revolution, people are more likely to be dependent on Machine Learning and Artificial Intelligent. Once people used to classify things, foods and images based on their intelligence. Doctors used to diagnose different diseases by undergoing invasive tests. Now people are more likely to predict images by AI. Doctors are also going for predictive models that can predict by analyzing the trends. Although the prediction sometimes is not 100% accurate as humans can predict. Still, the accuracy of the prediction is nearly 100%. For instance, food pictures order is as of late being utilized for diet checking purposes. Different infections are identified with consuming fewer calories like diabetes, coronary illness, hypertension, and a couple of malignancies. Exact appraisal of dietary caloric take is critical for studying the feasibility of the weight decrease process and that is the reason the food calorie estimation is getting significant in this cutting-edge local area. To further develop an individual's dietary patterns, an assessment of their dietary penchants is required, and this has been done actually beforehand, routinely with self-itemizing techniques. This strategy is blunder inclined and might be the reason for broad expense and furthermore extreme wellbeing harm. Accordingly, an automatic interaction of the food classification framework is mandatory. On that note, image processing frameworks have been taken into activity in many fields as of late. Clinical imaging, robot vision, and so on fields can be named as prevailing applications [1], [2].

However, a deep learning approach for the classification of foods can be the ultimate measure to track down the number of food calories by different ingredients consumed by a person on a daily basis [3]. Deep Learning, specifically Convolutional Neural networks (CNN) can also be used to detect Anemia, Jaundice for different types of diseases. Besides, by tracking the variety of food consumption, cardiovascular diseases can also be predicted [4]. Additionally, the conventional food varieties of a nation take after a few parts of its way of life, too [4]. One can find out about a country's food propensities and food culture by the excellence of their customary food handling and safeguarding technique. Only two works have been done in this field of Traditional Bengali Food Classification before this and in one of them, the authors used a pre-trained model for classification using an inadequate dataset [5]. In the second work[6], the authors built their own dataset and used one pre-trained model with their own scratch model. In this work, we will also be using the dataset of the later one and will be using 5 pre-trained models and compare the results with our two customized CNN models.

On the other hand, signal classification is another vital task. Specially, in the field of medical diagnosis. Nowadays, machine learning is being used for the classification of signals like EEG, ECG, PCG, EOG, EMG signals to early diagnose severe diseases such as epilepsy, strokes, tremor, sleep disorder, heart diseases, etc. In this paper, we will implement a model to predict Epileptic seizure disease from Electroencephalograph (EEG) signals by using a publicly available dataset[7].

Epilepsy is a transient brain dysfunction brought about by an unexpected anomaly of brain neurons [8], [9]. It is an illness with a high frequency and truly influences individuals' wellbeing. The determination of epilepsy essentially relies upon clinical history and electroencephalogram (EEG) examination,and around 80% of patients with epilepsy have specific EEG irregularities, which are shown as trademark waves of epilepsy. In the clinical conclusion of different seizures, EEG signal recognition assumes a pivotal part. Lately, more and more intelligent recognition techniques based on machine learning has been applied to the recognition of epileptic EEG signals [10]–[13].

II. Related Works

Numerous works have been done in the field of image processing and Signal classifications in recent years. Specially, the use of machine learning has enhanced the works to a great extent. In this section, we will be discussing the recent works that have classified images and signals to predict anomalies or their classes.

A. Image Classification with Machine Learning

The recent works [14]-[20] describe different methods to classify medical images, diagnose diseases and abnormalities detection in images using machine learning algorithms those are SVM, KNN, ANN, CNN, Logistic Regression. Sindu Divakaran et al. [14] proposed a system where dental anomaly can be classified using dental X-ray images with machine learning named SVM, KNN and ANN. They have used 500 dental images (250 for training and 250 for testing) to classify normal teeth and anomalous teeth, extracting 8 features which are skewness, smoothness, energy, entropy, homogeneity, performance, contrast, and correlation to detect 4 types of dental diseases.

Sajad P. Shayesta et al. [15] analyzed ultrasound images to classify malignancy of thyroid nodule where 210 have participated with FNA test report and 80 different features were extracted from sonographic images. Here, logistic regression (LR) algorithms were used as feature selector and classifier, respectively. For LR classifier gives an accuracy of 0.74, sensitivity of 0.85 and specificity of 0.60 for the training data whereas the validation dataset with an accuracy of 0.70, the sensitivity of 0.81 and specificity of 0.58.

Akinori Mitani et al [16] used 114000 eye retinal fundus images to classify Anemia using the deep learning method, to be precise, Tensor Flow. By using this dataset, they got 95% of accuracy while predicting Anemia for the patients. Inception-V4 architecture is a customized model of Convolutional Neural Network (CNN) in ImageNet and is developed and trained using Tensor Flow.

Deepak R. Parashar and Dheeraj K Agarwal [17] classified binary and multiclass Glaucoma by using 255x255 eye retinal images. They used 3 different datasets containing a total of 596 images. 2D Variational Mode Decomposition tool is used to decompose those images and further texture-based features were extracted. Finally, Support Vector Machine is applied to classify those images where they got 89.45% overall accuracy.

Roberta Avanzato and Francesco Beritelli [18] used disease diagnose from the image of Phonocardiogram. The images are classified into 5 classes on their dataset. They have taken 70% as training data and the rest of the 30% as validation. Their accuracy for the 5 classes is around 90% and further, they applied a recurrence filter which makes their result nearly 100% accurate. Where they decrease the time interval of the signal from 34 s to in between 10s to 20s.

Tessy Badriyah et al [19] classified two types of stroke such as ischemic stroke and stroke hemorrhage from CT Scan images where they applied a total of 8 machine learning algorithms such as K-Nearest Neighbors, Naïve Bayes, Logistic Regression, Decision Tree, Random Forest, Multi-layer Perceptron (MLP-NN), Deep Learning and Support Vector Machine. The maximum accuracy was obtained from the Random Forest algorithm which is 95.97% with recall 96.12%, precision 94.39%, and F1_score 95.39%.

The final paper [20] related to medical imaging is based on image classification with Machine Learning and Deep Learning which is a review paper, where all works have been shown and compared with each other in a time frame of twenty years. The authors also analyzed different supervised and unsupervised approaches to medical images. They explained the CNN model and how to classify medical images using CNN.

Image classification is not only being used in the medical field but also several sectors of our daily life. In industry, there are a lot of applications of image class prediction, detecting objects, analyzing reports and so on [21],[22],[23]. Yavor Lozanov et al. [21] used two different machine learning algorithms like KNN and SVM to classify fault in induction motor from grayscale images. Statistical features such as variance, std, skewness, kurtosis, and entropy are calculated. In this work, 100 images are classified into 3 different classes. The accuracy with KNN and SVM is 64.67% and 83.3% respectively. Another industrial application by Chakhung Yeung [22], who used 8000 images to classify the electrical equipment from their images. He performed image processing techniques to extract features and then applied different machine learning and deep learning model to predict the classes. LeNet, AlexNet, Deep learning – softmax and SVM are used and got maximum accuracy of 95% with Deep learning. Furthermore, N. Thamaraikannan and S. Manju [23] discussed and compared the existing machine learning algorithms on satellite imagery. In their review, they compared the machine learning algorithms such as SVM, Random Forest, Decision Tree, ANN, Naïve Bayes, DBScan, Mean shift and discussed the pros and cons of each algorithm and also compared their performance on those satellite images.

Moreover, different types of food and fruit images are also being classified for dietary purposes using different deep learning models. [6],[24],[25]. A. M. Uddin et al.[6] classified 7 types of traditional Bangladeshi food classification using transfer learning which is the VGG16 model of Convolutional Neural Network and a scratch model. A 6 layers CNN model is developed from scratch. In each of the layers, there are certain numbers of filters that are adjusted by the trial-and-error method to get the best accuracy. The mentioning thing of this article is the dataset developed and preprocessed by the authors where 2619 images were used as test data and 216 images are used as testing. For the customized model, they got an accuracy of 86% and for the built-in VGG16 model, the accuracy was 98%. M. S. Hossain et al [24] used two CNN algorithms are used to classify. There is CNN with 6 layers and another one is the VGG16 model. These two models are applied on two different datasets. The first one is containing clear pictures of fruits and the other one is an ambiguous picture of fruits. The accuracy of 99.49% and 99.75% were achieved on dataset 1 for the first and second models, respectively. The accuracy of the first and second models obtained 85.43% and 96.75%, respectively. Gianluigi Ciocca et al. [25] proposed a new dataset for food recognition with their customized dataset for diet monitory application where there are 1027 canteen trays images with 3616 foods of 73 classes. They used a convolutional neural network and got 79% of accuracy. They also used boundary-based and region-based segmentation of foods to extract features from the images. The model was trained with different food datasets. They also used other classifiers such as KNN, SVM apart from CNN. The accuracy for the other datasets is better than their food trays.

B. Signal Classification with Machine Learning

Signal classification is as significant as images in medical science. Specially, biomedical signals are directly related to our bodies. Many deadly diseases can be detected early by analyzing the signals using machine learning. Epileptic Seizure is one of the deadly diseases that can be diagnosed early after analyzing EEG signals [25]-[28].

Asma Baghdadi et al [25] introduced an LSTM model designed to address the chaotic nature of an EEG signal to predict pre-ictal and inter-ictal states. The model is evaluated on the publicly available CHBMIT database. An average sensitivity rate of 0.84 using a Raw EEG data segment as input to the LSTM model. This paper [26] is designed to predict the pre-ictal state of seizures using machine learning techniques. The features are extracted by The Dual Tree-Complex Wavelet Transform (DT-CWT), a signal processing technique. Frequency domain features and temporal domain features are extracted from the signals. Support Vector Machine with K-fold cross-validation is used as a classifier. This model gives 85.9% accuracy on real-time EEG signals with a prediction time of 60 minutes from the onset of an epileptic seizure.

Z. jhiang et al. [27] used a transfer learning approach with a novel linear model to predict epileptic seizures named TLSRLK which is based on both knowledge and label space transfer is proposed for multiclass epileptic EEG signal recognition. The Bonn dataset and TUH dataset are used in this experiment. This model is implemented on different datasets and proved to be more accurate than any other existing transfer knowledge algorithms like SVM, Au-SVM, Tr Adaboost, LSR, SRC, RLR, DLSR. In another study, P. Suguna et al. [28] used a publicly available dataset to predict epileptic seizures using the Fuzzy SVM Algorithm. Other algorithms such as KNN, Linear SVM, MLP were also used, however, the maximum accuracy of 79.65% was obtained by FSVM. There is a unbalance between the two classes. There are only 2300 seizure data in comparison with 9200 normal data.

EEG signals can also be used for detecting other abnormalities in the human brain. Different anomalies lead to different diseases like Alzheimer's Disease (AD) Mild Cognitive Disease etc.

Cosimo Ieracitano et al.[29] a classified dataset containing 189 EEG signals where 63 data with the Alzheimer Disease (AD), 63 for the Mild Cognitive Disease (MCD) and the rest data from the normal people(HC). The average time-frequency map is used with some statistical coefficient for feature extractions like mean, standard deviation, skewness, kurtosis, entropy etc. from alpha, delta, theta, beta sub-band. Finally, Logistic Regression, Multilayer Perceptron, Support Vector Machine are used to classify 2-ways EEG epoch classification task which is AD vs MCD and AC vs HC and got the accuracy of 95.76% and 86.84% respectively. N. Bahadoor et al.[30] proposed a method, that was evaluated with data including 785 EEG sequences contaminated by artifacts and 785 artifact-free EEG sequences collected from 15 intensive care patients. The obtained results showed an overall accuracy of 98%, representing the high reliability of the proposed technique in detecting different types of artifacts and being comparable or outperforming the approaches proposed earlier in the literature. In another study, C. Bhaskarachary et al.[31] analyzed the Electroencephalogram signal with two different machine learning algorithms such as Extra Tree Classifier and XGBoost to early diagnose Autism Spectral Disorder for children. The features were extracted from EEG signals and got an accuracy of 67.7% and 60% respectively with two classifiers. Besides, some transfer learning approaches are also applied to EEG Signal that is J. J. Bird et al.[32] showed transfer learning between EEG classification and EMG signal classification with both MLP and CNN methods. For EMG and EEG signal classification the accuracy was 84.76% and 62.37% respectively. However, when the EEG signal was classified with transfer learning using the MLP method where the pre-trained model was trained on EMG signal the accuracy increased from 62.37% to 93.82%. Likewise, a model trained on EEG and transferred to classify EMG, the accuracy increased from 84.76% to 85.12%. In the case of CNN, EMG to EEG transfer learning was fruitful, although EEG to EMG transfer learning was not significant which is decreased by 3.37%.

Taikyeong Jeong [33] investigated time series data of cognitive function of the brain obtained using a non-invasive technique on multiple channels using signal classification and analysis. The author collected signals using 19 channels by functional near-infrared spectroscopy (fNIRS) and EEG techniques while different working and resting conditions on 8 subjects. The author used shapelet and DTW (Dynamic Time Warping) classification techniques on brain signals to detect a disease or a disorder from the brain signal and used a machine-learning algorithm to predict the cognitive activity analyzing the brain signal pattern.

Apart from EEG, other biomedical signals can be used as disease predictors. Specially, those signals related to the heart such as ECG and PCG. In this study [34], the authors used a totally different technique to extract the features from the PCG Signals and detected HVD (Heart Valve Disease) using signal processing techniques which is Chirplate Transform. There were 4 types of HVD that are classified based on the features named Local Energy (LEN) and Local Entropy(LENT). These features are evaluated from the TF Matrix of the PCG Signals. A total number of 1000 data were used. Finally, they used a multiclass composite classifier to classify 4 types of HVD. They used 10-fold cross-validation and got average accuracy of 98.33%.

In this article [35], the authors designed a customized Convolutional Neural Network with 4 layers to get the maximum number of accuracy for three different classes from ECG signal. Here one class is normal and the other two classes are abnormal. While predicting the normal class, the classifier was 99% successful while for the other two, the accuracy was

100% and 96% respectively. There are 10800 samples, that are divided into 3 subgroups. 30% sample was separated for testing where 40% is for training and 30% is for validation. Finally, overall accuracy with the customized CNN Model is 98.33%.

III. Methodology

In both of the work of this paper, traditional Bangladeshi food image classification and Epileptic Seizure Detection from EEG signal, we used Keras, along with Tensorflow 2.0 with Python v3.6.9.

A. Image Classification

Figure 1 shows the steps of this work which are followed to classify food images. Classification of the images both with transfer learning and a new CNN model are depicted simultaneously in the flowchart.

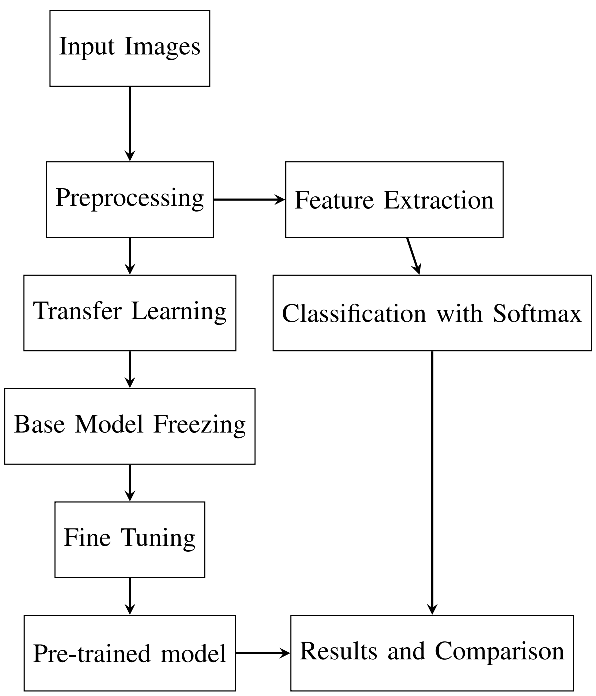

Figure 1: The flowchart of proposed work Image Classification.

1) Food Image Dataset Description: The dataset used from a research paper [6] where there are a total of 2835 traditional Bangladeshi food images. Among them, 2619 images are used as training images, and the rest of 216 images are used as test images. The image size was between 300x300 to 720x1280. The details of the dataset are depicted in table I.

2) Image Pre-processing: As we are using a small dataset in CNN, there is a huge chance of overfitting data in testing data. To avoid this, we used some pre-processing and augmentation techniques. Firstly, we changed the size of images in 128x128 and 224x224 as our different images have different sizes which result in reducing the computational power. Again, we are using the images in RGB color scale where pixel range between 0 to 255 with 3 layers. All the pixel from 0 to 255 is changed to 0 to 1. Another process of enhancing

TABLE I
FOOD IMAGE DATASET FOR IMAGE CLASSIFICATION

Classes	Train Data	Test Data
Class_1	258	21
Class_2	219	18
Class_3	423	35
Class_4	516	43
Class_5	303	25
Class_6	468	38
Class_7	432	36
Total	2619	216

data is images augmentation which is an image manipulation method to create different versions of the same image to expose the model to a wider array of the training example. The image augmentation is done by zooming, shifting the images horizontally and vertically with different parameters. Rotation is also used to augment the image dataset.

3) Feature Extraction with Convolutional Neural Network.: CNN provides a high margin of accuracy in image recognition and classification. Its model consists of multiple layers connected with multiple neurons and gives output after passing through a fully connected layer. In the first layer, CNN learns the basic shape of input and then gradually learns the other features of the image in the deeper layers. Unlike machine learning methods, CNN does not require any feature extractions from input manually. CNN automatically extract feature from data before feeding the data to fully connected layers. It is comprised of convolutional layer, activation function, max-pooling layer, fully connected layer, and so on where each layer performs different tasks on the input data. In this image classification, the dataset is uploaded in google drive and each class of image is separated into 7 different folders. CNN automatically detects the classes with the features and predicted the classes. of more than 1000 classes. For every model, we froze the base model and trained with our dataset by changing the input and output layer. Finally, train the model again by lowering the learning rate to get better accuracy.

4) Classification with softmax: Softmax is an activation function that is usually put as the final layer of a CNN model. This function converts the output of a neural network to a probability distribution over predicted output classes. The probability distribution fall between the scale of 0 to 1. The highest probability is classified as the output. Mathematically,

$$softmax(x)\_i = \frac{exp(x_i)}{\sum_j exp(x_j))}$$

5) Transfer Learning: Transfer learning is a machine learning method where a model developed for a task is reused as the starting point for a model on a second task. Transfer learning is related to problems such as multi-task learning and concept drift and is not exclusively an area of study for deep learning. It is common to perform transfer learning with predictive modeling problems that use image data as input. This may be a prediction task that takes photographs or video data as input. In this work, we have used 5 different pre-trained models as transfer learning methods. The models are VGG16, VGG19, Xception, ResNet50 and InceptionResNetV2. All of the models trained on the 'ImageNet' dataset which is the biggest dataset containing 14,197,122 annotated images of more than 1000 classes. For every model, we froze the base model and trained with our dataset by changing the input and output layer. Finally, train the model again by lowering the learning rate to get better validation accuracy.

B. Signal Classification

Figure 2 depicts the steps of EEG signal Classification to predict epileptic seizures using the CNN model. In the very first step, we uploaded the dataset. The dataset is in the form of a CSV file where all features were extracted and pre-processed. After that, A model with multiple layers is built including the input layer, dense layer, batch normalization layer, and output layer. Then, the model was trained with the dataset. For training, the dataset is separated by 80% and the rest of 20% data are used for validation purposes. Finally, after 100 epochs, the training is completed and output is classified through sigmoid function to predict epileptic seizure. The sigmoid function represents probability. The output of this function is real numbers with a range is 0 to 1. Mathematically,

$$h_\theta(x) = \frac{1}{1 + e^{-}\theta^{T}x}$$

1) Dataset Description: The dataset consists of 5 different folders, each with 100 files, with each file representing a single subject/person. Each file is a recording of brain activity for 23.6 seconds. The corresponding time-series is sampled into 4097 data points. Each data point is the value of the EEG recording at a different point in time. So we have total 500 individuals with each has 4097 data points for 23.5 seconds. It is divided and shuffled every 4097 data points into 23 chunks, each chunk contains 178 data points for 1 second, and each data point is the value of the EEG recording at a different point in time. So now we have 23 x 500 = 11500 pieces of information(row), each information contains 178 data points for 1 second(column), the last column represents the label y 1,2,3,4,5. The response variable is y in column 179, the Explanatory variables X1, X2, ..., X178, y contains the category of the 178-dimensional input vector. Specifically y in 1, 2, 3, 4, 5:

5 - eyes open, means when they were recording the EEG signal of the brain the patient had their eyes open

4 - eyes closed, means when they were recording the EEG signal the patient had their eyes closed

3 - Yes they identify where the region of the tumor was in the brain and recording the EEG activity from the healthy brain area

2 - They recorder the EEG from the area where the tumor was located

1 - Recording of seizure activity

All subjects falling in classes 2, 3, 4, and 5 are subjects who did not have epileptic seizure. Only subjects in class 1 have epileptic seizure. Our motivation for creating this version of the data was to simplify access to the data via the creation of a .csv version of it. Although there are 5 classes most authors have done binary classification, namely class 1 (Epileptic seizure) against the rest

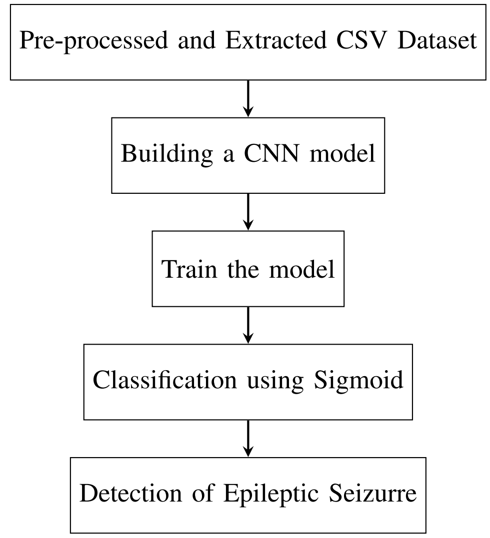

Figure 2: The flowchart of proposed work for Epileptic Seizure Detection.

IV. Results

A. Result for Image Classification

Although a total of 5 transfer learning methods are used, we got only the best accuracy in VGG19 and VGG16 model. Table II shows the detailed results of VGG19 while predicting 216 images of 7 classes. Class_4 is making the average precision and accuracy lower than the other classes.

TABLE II
THE RESULT FOR TRANSFER LEARNING WITH VGG19

	Precision	Recall	F1_Score	Support
Class_1	1.00	0.90	0.95	21
Class_2	0.88	1.00	0.93	43
Class_3	0.92	0.96	0.94	25
Class_4	0.85	0.94	0.89	18
Class_5	0.92	0.92	0.92	38
Class_6	1.00	0.83	0.91	35
Class_7	1.00	0.97	0.99	36
Average	0.94	0.94	0.94	216
Accuracy	0.94			

Table III illustrates, the outcome of the Scratch CNN model that we built from scratch. The Overall accuracy is 78% for this model. This accuracy could have been better if we dropped class_4 from our dataset. This class decreases the average value of precision, recall, accuracy, and F1 score.

TABLE III
THE RESULT FOR CNN SCRATCH MODEL WITH IMAGE SIZE 128X128

	Precision	Recall	F1_Score	Support
Class_1	0.95	0.95	0.95	21
Class_2	0.78	0.93	0.85	43
Class_3	0.79	0.76	0.78	25
Class_4	0.59	0.56	0.57	18
Class_5	0.74	0.66	0.69	38
Class_6	0.62	0.60	0.61	35
Class_7	0.97	0.94	0.96	36
Average	0.78	0.77	0.77	216
Accuracy	0.78			

Table IV and Table V depicts the comparison among the five pre-trained model average accuracy via transfer learning and CNN scratch model with two different image sizes.

TABLE IV
THE COMPARISON WITH TRANSFER LEARNING AND BASE MODEL

Results	**Transfer Learning**		**CNN Scratch Model**
	VGG16	**VGG19**	**224x224**
Accuracy	**92%**	**94%**	**73%**
Recall	**90%**	**93%**	**71%**
Precission	**94%**	**94%**	**74%**
F1_Score	**92%**	**93%**	**71%**

TABLE V
THE COMPARISON WITH TRANSFER LEARNING AND BASE MODEL

Results	**Transfer Learning**			**CNN Scratch Model**
	ResNet50	**Xception**	**Inception ResNetV2**	**128x128**
Accuracy	**61%**	**65%**	**75%**	**78%**
Recall	**61%**	**65%**	**68%**	**77%**
Precission	**64%**	**70%**	**76%**	**78%**
F1_Score	**60%**	**64%**	**71%**	**77%**

The differences between this work and the same work that has been done using the same dataset is shown in the table VI.

TABLE VI
COMPARATIVE ANALYSIS BETWEEN PREVIOUS WORKS AND THIS WORK

Paper Reference	Methods	Dataset	Accuracy
N. Tasnim et al.[5]	CNN	Dataset containing small amount of images	83%
A. M. Uddin et al. [6]	CNN and 1 Transfer Learning	Dataset containing 2835 Images	86% with CNN and 98% with VGG16
This work	CNN and 5 transfer learning	Dataset containing 2835 Images	78% with CNN and 94% with VGG19

B. Result for Signal Classification and Seizure Prediction

We tried to predict seizure from EEG extracted signal from this second portion of the work and found the result as in Table VII. The average accuracy is 98% which is higher than the previous all works with this dataset. The previous results were up to 97%.

TABLE VII
THE RESULT FOR PREDICTIVE RESULTS OF EPILEPTIC SEIZURE

	Precision	Recall	F1_Score	Support
Non-Seizure	0.98	1.00	0.99	2298
Seizure	0.99	0.90	0.94	577
Average	0.98	0.95	0.96	2875
Accuracy	0.98			

Table VI demonstrates the comparative study between recent works and this work with deep learning. It can be seen that this work has the highest accuracy compared to others.

TABLE VIII
COMPARATIVE ANALYSIS BETWEEN PREVIOUS WORKS AND THIS WORK BASED OF EPILEPTIC SEIZURE CLASSIFICATION USING EEG

Paper Reference	Methods	Dataset	Accuracy
Asma Baghdadi et al [25]	LSTM model	public CHBMIT database	Sensitivity 84%
I. Bhattacharjee[26]	SVM to classify and Dual Tree-Complex Wavelet Transform (DT-CWT)for feature extraction	They collected the data for 60 minutes from the brain signals	85.9% Accuracy
Z. jhiang et al. [27]	Transfer learning	Bonn dataset and TUH dataset	65% to 82% for different methods
P. Suguna et al. [28]	Fuzzy SVM Algorithm	2300 seizure 9200 normal .	79.65%
This work	Deep Learning	500 data	98%

V. CONCLUSION

In this work, two different works have been done separately. In image classification with deep learning, to be precise, with Convolutional Neural Network the food images are classified into 7 classes. For the classification, 5 pre-trained models were used with 1 customized CNN model that is built from raw. The results of transfer learning are higher than the scratch model because those models were trained on the ImageNet dataset which is consists of millions of images from thousands of image classes. However, in our scratch model, we used only 2619 images to train and 216 images to validate the model. Thus, this deference occurs in accuracy, precision, recall and f1_score. On the other hand, In the case of signal classification with deep learning, we detect EEG signals from a publicly available dataset that was pre-processing and extracted features from EEG signal as CSV file. We just build a model and trained the model with the dataset and got a validation accuracy of 98%. The reason for higher accuracy is the dataset is huge where there are 11500 rows and 178 columns, which means there are 11500 instances with 178 extracted features. Thus, the result is almost near to 98%.

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