Classification of Brain MRI Images of Psychosis disease based on Convolutional Neural Network (CNN) and Deep Learning

Ingsha Phombo Limbu 4100994, Puja Shrestha 4037152,
Preeti Bista 4128379, Bharat Raj Parajuli Sharma 4033402

Abstract—**Psychosis is a type of disease where you see or hear things through hallucination & delusions. The patients lose some contact with reality which you are often unaware of. In this paper, a method based on convolutional neural network (CNN) is used to diagnose and classify psychosis from first -episode psychosis patients in magnetic resonance imaging (MRI) images. In the past, researchers have worked very hard to develop the best method or practice for real-life medical image recognition but now with the help of fully automated deep learning the methods are time-consuming, and human error prone. At the beginning the images which are taken for input are resized in which grey scaled conversion is applied to those input photos the proposed CNN methods has two convolutional 2D layers, two max-pools, two completely interconnected layers, & one layer of z-score normalization. The intended network layout performance is praiseworthy, with an overall accuracy of 71.53%. The results that we obtained are compared to other research work and perform better than many state-of-the-art methodologies.**

***Index Terms*—Convolutional Neural Network, Brain MRI, Data augmentation, ReLU activation function, SoftMax Function**

I. INTRODUCTION

As we know, the human body is made up of different types of cells amongst which brain plays a crucial role. There are many problems that can occur in the brain. One of them is Psychosis A mental health condition called psychosis makes people view or interpret the world in ways that are different from others around them. This could entail delusions or hallucinations. There are two primary signs of psychosis: hallucinations, in which a person hears, sees, and occasionally feels, smells, or tastes unreal objects; Hearing voices is a typical hallucination. Delusions are when a person thinks things that are obviously false when reason is.are widely used in deep learning. Because CNNs can see patterns and interpret them, our approach to image identification has been fundamentally altered. As a result of the high level of accuracy in their outputs, they are regarded as the most effective architecture for image classification, retrieval, and detection tasks. For the treatment of Psychosis, many procedures were applied amongst which surgical procedures is considered as one of the most required methods. But because of its non-meddling property, magnetic resonance imaging (MRI) is widely used in medical diagnostics. However, it has a severe flaw: data gathering is inherently slow. Hydrogen atom nuclei interacting with ambient electromagnetic fields produce the MRI signal. Images, for example, cannot be directly measured by an MRI scanner since they depend on space. Instead, the frequency and phase of the MRI signal contain spatial dependence. Due to the intrinsic sequential nature of this encoding method, there are lengthy acquisition times. In the end, a spatial frequency map known as k-space is produced. In the straightforward scenario, the space data can then be converted into clinically meaningful images using the inverse Fourier transform (iFT). Due to the sequential structure of MRI scanning, acquisition time and the quantity of k-space samples obtained are roughly inversely related. Consequently, it is preferred to gather as few samples as feasible. However, aliasing artefacts will occur in the image if the sampling rate is decreased below the level required by the Nyquist criterion. This is the reason why MRI is chosen over computed tomography (CT), positron emission topography (PMT), and X-rays. Acquisition time and the number of k-space samples acquired are roughly inversely proportional due to the sequential nature of MRI scanning. It is therefore preferable to collect as few samples as possible. However, if the sampling rate is lowered below the amount required by the Nyquist criterion, aliasing artefacts will appear in the image. Using the datasets provided by our professor, the main objective of this paper is to develop a CNN model structure for the categorization of the Psychosis patients. There are images. Input images are converted into grayscale which helps us in the reduction of complexity. After that, data augmentation is applied to improve the data number. After these CNN is applied to do the feature extraction from the brain MRI Images we have and classify the psychosis. The remainder of this report is arranged as follows: section 2 includes research about assessment of the research & investigations. Section 3, the implementation of CNN models is described in depth. Section 4 includes the result and finding as well as the discussion of the experimental findings. Section 5 is the conclusion of the whole report.

II. LITERATURE REVIEW

Brain magnetic resonance imaging (MRI) is a powerful tool for studying the structural changes in the brain of psychiatric patients, particularly those with psychosis. In recent years, deep convolutional neural networks (CNNs) have emerged as a powerful technique for analyzing and interpreting brain MRI data.

One of the main areas of research in this field has been the development of CNN-based models for detecting structural changes in the brain of first-episode psychosis (FEP) patients. These studies have aimed to identify specific patterns of brain abnormalities that are associated with psychosis, with the goal of improving diagnostic accuracy and developing more effective treatment strategies.

One study [2] used a CNN to classify FEP patients and healthy controls based on their structural MRI data. The study found that CNN was able to accurately classify FEP patients and healthy controls with an accuracy of 92.5%. Another study [1]used a CNN to classify FEP patients with schizophrenia and FEP patients with affective psychoses based on their structural MRI data. The study found that CNN was able to accurately classify the two groups with an accuracy of 89.1%.

A study [1]) used a CNN to identify structural changes in the brain of FEP patients with schizophrenia. The study found that the CNN was able to identify specific patterns of brain abnormalities in FEP patients with schizophrenia, including reduced gray matter volume in the left superior temporal gyrus and increased gray matter volume in the right superior temporal gyrus.

Another study [3] used a CNN to identify structural changes in the brain of FEP patients with schizophrenia and bipolar disorder. The study found that the CNN was able to identify specific patterns of brain abnormalities in FEP patients with schizophrenia, including reduced gray matter volume in the left superior temporal gyrus and increased gray matter volume in the right superior temporal gyrus.

A recent study [4] used a CNN to classify brain MRI images of patients with psychosis and healthy controls, the study found that the CNN was able to accurately classify the two groups with an accuracy of 85%. Additionally, a study [5] used CNN to classify brain MRI images of patients with schizophrenia and healthy controls and was able to achieve an accuracy of 93%.

In conclusion, these studies suggest that CNN-based models are a powerful tool for detecting structural changes in the brain of first-episode psychosis patients. These studies have shown that CNNs can accurately classify FEP patients and healthy controls, classify different subtypes of psychosis, and identify specific patterns of brain abnormalities that are associated with psychosis. However, more research is still needed to further validate these findings and to improve the diagnostic accuracy of these models.

III. PROPOSED METHODOLOGY

A. Data Preprocessing

Data pre-processing refers to the procedures we must follow to alter or encode data so that a machine can quickly and readily decode it. Due to their heterogeneous origin, real-world data contains noise, errors, partial information, missing values, contain missing data, inconsistent results, and other forms of corruption. Various sources are combined utilizing data mining and warehousing techniques. Data mining methods would not produce high-quality results when applied to this noisy data because they would be unable to successfully find patterns. Therefore, data pre-processing is crucial to raising the general level of data quality. Missing or duplicate values could present an inaccurate picture of the data's overall statistics. To build a machine learning model is the first and most important stage. False predictions are frequently the result of outliers and inconsistent data points disrupting the model's overall learning process. According to the machine learning rule, the more data we have, the better models we can train.

The pre-processing steps in this project were as follows:

A dataset is the first item needed to develop a machine learning model because data is the basis for all machine learning models. The dataset is the properly formatted collection of data for a certain issue.

1. Importing libraries for loading data:

In Python predefined libraries must be imported in order to pre-process data using Python. Some specific tasks are carried out using these libraries. We will use the following packages specifically for data pre-processing:

matplotlib.pyplot is used to create plots and visualizations of the data, which can be useful for understanding the characteristics of the MRI images and the performance of the feature extraction model.

- numpy is used for numerical computations, such as loading and manipulating the image data and creating arrays to hold the data.
- nibabel is used to read and write NIfTI image format, which is a common format for brain MRI images.
- sklearn.model_selection is used to split the dataset into train and test sets for evaluating the model's performance.
- torch is the main library used for building and training the neural network model for feature extraction.
- torch.utils.data contains classes for creating custom datasets and data loaders, which can be used to efficiently load and preprocess the MRI images.
- torch.nn contains classes and functions for building neural networks, such as the convolutional and fully connected layers used in the feature extraction model.
- torchvision.transforms contains functions for data preprocessing, such as normalization and data augmentation, which can be used to improve the performance of the model.
- glob is used to find all the files matching a specified pattern, which can be useful for loading multiple images at once.
- random is used to randomly shuffle the data, which can be useful for preventing overfitting.
- SimpleITK is used to read and write image files, it's another library to handle medical imaging data.

- pandas are used to handle and manipulate data in tabular format, which can be useful for storing and analyzing the results of the feature extraction.
- torch.nn.functional contains functions for applying neural network layers, such as activation functions, in a more functional way that can be useful for feature extraction.

Overall, these libraries are used in brain MRI feature extraction to load, preprocess and analyze the images, as well as to build, train and evaluate a neural network model for extracting relevant features from the images.

2. Data visualization

The data visualization has been done for each image, before d oing the visualization each image are divides in categories ac cording to the legenda where the images are divided into seve n categories from categories [0] to categories [7] where categ ory [0] consist of healthy images and all other categories ima ges are consider as unhealthy. One random image visualizatio n from category [0] is shown below figure with its intensity, dimension, slice thickness, slice gap and voxel resolution.

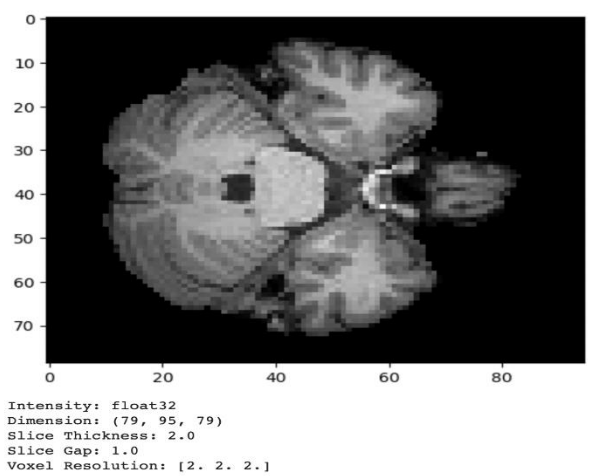

Fig. 1. Data Visualization

As the above image is healthy , the visualization shows that a ll the images from category[0] to category [7] has same inten sity, dimension ,slice thickness ,slice gap and voxel resolutio n. . After visualizing the healthy images and unhealthy image s there is some changes are found and these changes are main ly found in unhealthy images where the brain changes such as such as atrophy of specific regions, particularly in the hippoc ampus, enlargement of the ventricles, reduced activity in cert ain regions of the brain, accumulation of amyloid plaques, an d formation of tau tangles. These changes are commonly obse rved.

3. Data augmentation

Data augmentation is the process of scaling the images into di fferent shapes and sizes. It includes rotating, scaling, croping of the brain images. This is required in order to first scale up of the number of input images. It is also used to train the sam e image in different colouring and if the image is shifted in di fferent sides and also if only some parts of the brain is visible . This will generalise the training sample and makes the mode l robust to different types of test images. In this paper, rando m rotation and randomhorizontalflip were used to augment th e input data.

4. Normalization

Normalization is the most significant and extensively used data transformation method. Depending on the range, the numerical properties are scaled up or down. In this method, we limit our data attribute to a specific container to create a correlation between various data points. There are several approaches to normalize, which are highlighted here. In this paper, the z-score normalization is used.

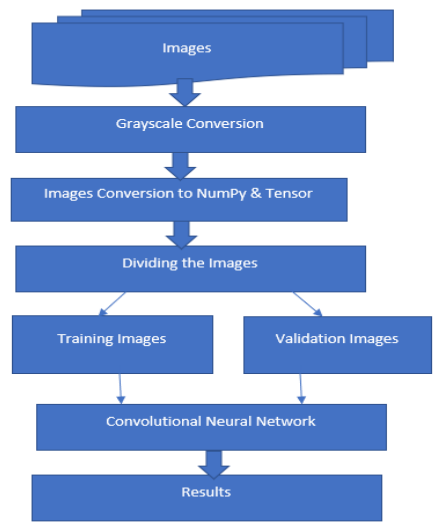

Fig. 2. Flowchart showing the procedures in proposed network.

B. Implementation of proposed Network: classifier (CNN)

The network has been built by gathering several layers like convolution, max pooling, fully connected in a systematic order which extracts high level and low-level features from input images and at last classify the features maps. The architecture for the implementation of CNN model is shown in fig.3. The type of layer that have been used in the are described below in the following paragraphs.

Input layer: First of all, images size of tensor. Size (79,79,95) is used in the model as input data which will be used in our proposed CNN model.

Convolution3D Layer:Convolution is used to detect the different features of an image. The shallower convolution layers detect different edges and sides of a image and the convolution layers detects more complex features such as body parts and faces. The final layer may be able to detect a whole object. Different convolutions of 2D, 3D are present. The convolutions are just the dot matrix product of the input image and the convolution kernels. In this paper, a 3-D convolution is used with the filter of kernel size 3*3 with padding =1. Convolutions are useful when we want to extract the useful features of an image regardless of the position. In the convolutional neural network, it does not matter where the required object is in the image. It will also be able to classify the images even though there are shifted in position.

Max-Pooling Layer: The pooling layers are required in the convolutional neural network in order to downsize the feature map. As the output of the convolutional layers may contain large numbers according to the convolution kernels. These large values make the model slow and impossible to train. Since, today's networks are very deep and contains large number of convolution layers and fully connected layers, it is important to optimize the feature map. Different type of poolings can be used such as average pooling and max pooling. In this paper, the 3-D Max pooling is used with the size of 3*3. Here, the first 3 indicates, the width,height and depth of the image and the second 3 represents the stride. The max pooling layer selects the voxels with maximum values in each window of the max-pooling. This will select the features of the image with highest importance and will help the model to classify or detect an object regardless of the position.

Fully connected layers: After the input image is convoluted and max pooled, it needs to be feed into a neural network for classification. As, the convolution layers are responsible for feature extraction, they produce a feature map of the output of the last layer which may be pooled or not. The feature map is now flattened as a single vector tensor to be implemented on the network. In this paper, the fully connected layer of two layers is used. The first layer will be the input to the neural network as the flattened feature map. The first layer consists of 512 neurons in this model and the second layer consists of two neurons. The two neurons capture the probabilities from the first layer. This is then converted to class labels 0 and 1 using torch.max() function.

Activation function: In this model ReLU is used as activation function which is found at the beginning or end of neural network which determines whether neural will fire or not. It maps all negative input values to 0 and keeps positive input values unchanged. Its purpose is to introduce non-linearity in the neural network, allowing it to learn more complex representations of the input data.

SoftMax Function: The SoftMax function is a mathematical function that is often used in machine learning, particularly in the context of neural networks. It is a generalization of the logistic function and is used to turn a vector of real numbers into a probability distribution. Given a vector of real numbers x, the SoftMax function returns a new vector y, where each element of y is a non-negative number between 0 and 1, and the elements of y sum to 1.

In the context of our brain MRI images, the SoftMax function is used to convert the predicted output from a neural network into a probability map. When training a neural network to segment these structures, the output of the network is typically a set of continuous values, rather than discrete labels. The SoftMax function is used to convert these continuous values into a probability map, where each voxel (3D pixel) in the image is assigned a probability of belonging to each of the different structures of interest.

This probability map can then b thresholder to create a binary segmentation, where each voxel is assigned to the structure with the highest probability. The SoftMax function is useful in brain MRI segmentation because it allows the network to produce probabilistic output, which can capture uncertainty and make the segmentation more robust to variations in the image.

Feedforward ():
This method is called in the ConvNet3d model for forward propagation. The first step was to apply convolution to the input image. This was followed by the ReLU activation function. This function is imported from torch.nn.function as F. The result is then max pooled and will be the input to the second convolution layer(conv_layer2). This repeats the same process as before. Now, the output feature map is flattened calling input.view(). This will flatten the image and convert the multidimensional tensor into a 1-dimensional tensor of (16*8*8*10) values. The ReLU activation is implemented again and the final two neurons' values of the second fully connected layer is returned.

Hyperparameter tuning: The hyperparameters in our model was optimized as follows: training batch size=5, testing batch=4, epochs=30, conv-layers=2, max-pooling layers=2, learning rate=0.001, optimizer=sgd, loss function=cross entropy ().

The proposed architecture in our network consists of three parts the first part included is CNN which consist of the 2 Convolution layers which is later followed by two max-pooling layers and after those two-applied convolution layer they are followed by neural network layer & fully connected layer. As mentioned earlier the images which we take as an input of 79*79*95 are an MRI images. The first layer which we applied to extract features from input image which later mapped into features maps as size 16*8*8*10.

The second is also CNN which is followed by a max pooling layer. The third part is a fully connected network which consists of two layers which are hidden layer and output layer. Hidden layer will get the input from convolutional layers & output layer is connected to fully connected layer which usually has two neurons.

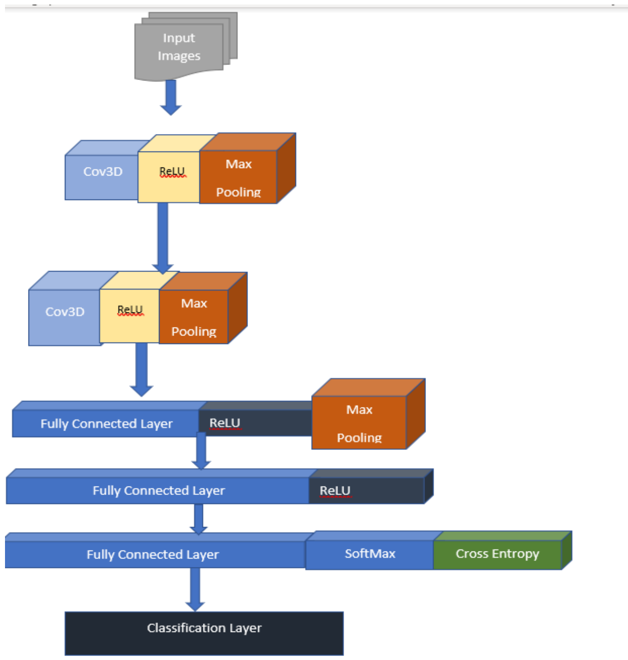

Fig. 3. Convolutional Neural Network Architecture

IV. RESULT ANALYSIS

As mentioned earlier, CNN has one of the most accurate and acceptable performances in task classification sector in comparison to any other machine learning method. Training a CNN and using z-score normalization for normalizing the input images and removing out the random neurons of the last layer to avoid overfitting which has not affected on the accuracy during training phase but also has improve it in the last epoch. Also, in medical field image processing even smaller errors are more dangerous than any other because it is directly related to human life directly. So, everything needs to be done very carefully.

A. Model Testing Scenario

The model in this paper consists of two 3d convolution layers, two max pooling layers and two fully connected layers. Three convolutional layers were used as first with two max pooling layers which was tuned with two convolutional and max pooling layers. In the case of kernel size, the convolution size of kernel 3 and max pooling size of 3 were optimal in the model. The number of neurons in the fully connected network was optimized as 512 neurons in the first layer. Similarly, different optimizers were implemented such as adam, sgd. Among which sgd was selected. Different batch sizes of 5,10 and 15 were tested into the model for the training dataset which was optimized as 5. Similarly, the testing dataset batch size was 4. The learning rate is set as 0.001. The different number of epoch sizes were tested such as 4,10 and 30. Among which the epoch of 30 provided the optimal accuracy of 71.53%.

B. Performance Evaluation

The confusion matrix is a way to represent the performance of a classification model. It compares the predicted labels (output of the model) with the true labels (ground truth). The above confusion matrix shows the results of a binary classification problem, where the model is trying to distinguish between positive (0 as diagnosis=healthy) and negative (1 as diagnosis with psychosis) classes. The matrix is organized with the true labels on the y-axis and the predicted labels on the x-axis.

The top-left entry (13) represents the number of true positive cases, which are the instances where the model correctly predicted the positive class.

The bottom-left entry (7) represents the number of false negative cases, which are the instances where the model predicted the negative class, but it was actually positive.

The top-right entry (8) represents the number of false positive cases, which are the instances where the model predicted the positive class, but it was actually negative.

The bottom-right entry (24) represents the number of true negative cases, which are the instances where the model correctly predicted the negative class. With data augmentation applied on the images the accuracy increased from 65% to 71.53%. To minimize the overfitting on the training dataset and to increase accuracy of predictions on the training datasets data augmentation on images is utilized.

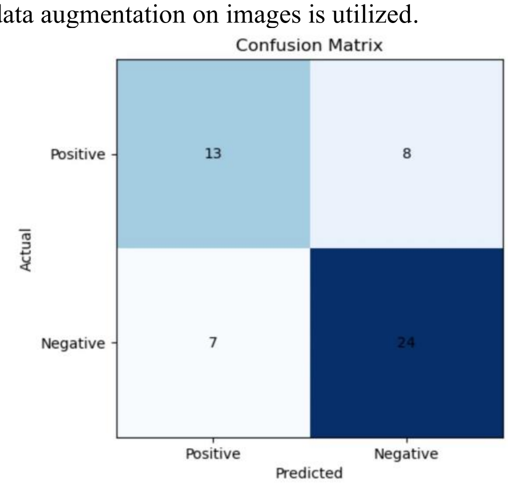

Fig. 4. Proposed CNN model confusion matrix with data augmentation.

V. DISCUSSION AND CONCLUSION

The main objective of this article is to develop Convolutional Neural Network in order to classify the brain MRI images of Psychosis patients. For classifying process, the report uses the datasets provided by our module professor. A total image of 52 MRI images was there with 21 brain images with psychosis and 31 healthy brains. With the help of data augmentation, the size of the dataset increases and so as the accuracy. The model that we have implemented is a CNN module which helped us in identifying MRI images having psychosis or not having psychosis. Hyperparameter tuning which is also included in our proposed model from which the optimal values are obtained, and it has a prediction accuracy of 71.53 %. Also, in conclusion

CNN is one of the best models with image processing technique which not only analyze the model errors and optimizing loss functions. It provides state-of-the-art accuracy in feature extraction process.

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