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Unveiling Cosmic Enigmas: Fast Radio Bursts Analysis Using Machine Learning and Convolutional Neural Networks

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Abstract: Universe has many mysteries like Pulsars, dying stars, supernovae, and fast radio bursts (FRB) are known as astronomical phenomena or events, which can be recognized by using different ML and DL approaches. Here one of the mysteries of fast radio busts events was discovered by using machine learning and convolution neural network with published data from the voyager radio telescope at frequencies from 8418.457MHz to 8421.38671 MHz. Also the analysis of different algorithm like CNN, LogReg, Decision Tree, Extra-Tree, Random Forest and LGBM to recognized radio emit from miscellaneous light across the electromagnetic spectrum and due to remonstrance advances in radio astronomy, the study of emitted objects in radio waves is the biggest scope of the study, which will be helping us to reveal the mysteries of the Universe.

Keywords: *Fast Radio Burst, Deep Learning, Machine Learning, Space Telescope, Convolutional Neural Network, Neural Network, Random Forest, Radio Frequency Interference, Transfer Learning, Computer Vision, Incremental Learning, LogReg, Decision Tree, Extra-Tree, Random Forest, LGBM.*

1. Introduction

The first fast radio burst has been described by the Lorimer Burst in 2007 with “FRB 010724” data set which was found in archived data recorded by the Parkes Observatory on 24 July 2001(Lorimer et al. 2007) [1]. Since then, many FRBs have been found in previously recorded data. On 19 January 2015, astronomers at Australia's national science agency (CSIRO) reported that a fast radio burst FRB had been observed for the first time live in a milky way, by the radio telescope called Parkes Observatory, which is located 20 KM from north of the city named as Parkes in Australia. Further, many FRBs have been detected in real-time by the CHIME radio telescope since it became operational in 2018, including the first FRB detected from the Milky Way in April 2020 which is one of the biggest achievements for humans [2]. Today’s radio telescope has more power with capacity for capturing the data like 1 PB, which required advanced algorithms and proceeding powers to handle such larger amount of that to analyze and detect different events along with avoiding noise, and noise reduction are the one of major challenge with data since its take a lot and length of time to process it but new advance radio telescope handing such data easily and we can set out parameter on radio telescope to get enhance data. As per characterize analysis on fast radio bursts in-universe by considering dispersion measures from bright, millisecond-duration radio transients of wave are called fast radio bursts event [3].

Machine learning and Convolutional Neural Network algorithms has progressive capability to determine signals with more values. Many different methods are introduced in literature to reduce the model’s false positive values, to increase the efficiency as well. Their compliance before radio frequency interference (RFI) enable radio telescope for noise reduction without human intervention [4, 5]. Furthermore, we can use it for the classification of various events in the milky way the galaxy, and it needs to analyze data in real-time to monitoring upcoming events. Data collected at radio telescope are in binary format with ‘.fil’ file and has a very larger volume of data[6]. Telescopes can store daily more than 1PB data, which is big challenge for stores along with maintenance of such data. Deep learning and quantum computer processing are helpful for the processing of huge telescopic data [7].

Below is the list of telescopes exiting on our earth for collecting data in many regions data will be an archived daily and keep it safe [2] and most the radio telescope has A parabolic antenna is an antenna that uses a parabolic reflector, a curved surface with a parabolic cross-section, to direct radio waves toward the receiver at its focus. The common shape is a parabola and is called a parabolic antenna [2].

1. Very Large Array VLA Radio Telescope

This radio telescope is based in the USA and it has 27

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Cass-grain antennas, every antenna has a Diameter-Meters of 25 which can be moved along with a Y-shaped rail system.

2. Arecibo

From the US Puerto Rico, one of the biggest parabolic antennae in 2016 at 305 Meters-Diameter can b e moved in a different direction in the sky.

3. GBT - Green Bank Radio Telescope

Well, know Green Bank radio telescope in the USA also have 43 Meters-diameter parabolic antenna and this station can collect data PB each day.

4. Atacama Large Millimeter/submillimeter Array Radio Telescope (Chile)

Chile’s radio telescopes have 7 to 12 installed Atacama Desert parabolic antennas which have 5000 meters range above sea leave for high radio frequencies.

Built 35 kilometers from Cagliari, this radio telescope uses a 64-meter diameter parabolic antenna (one of the best of many radio telescopes in the world) that allows recording at high frequencies (up to 100 GHz).

9. Lovell Radio telescope

The antenna with a periphery of 76 measures, this device is one of the largest radio telescopes in the world with a moving glass. It's located in Jodrell Bank (England) and is part of the English interferometer system MERLIN.

10. Parkes Radio Telescope

Parkes Observatory is located in the southeast of Australia and uses a large parabolic antenna with a diameter of 64 meters. In addition to radio astronomy, it also serves to collect Apollo 11 months' broadcasts.

5. FAST Radio Telescope

China also developed the 5K Meters Aperture Radio Telescope (FAST) in southwest China. It consists of a solid dish with a diameter of 500 meters made of a natural depression of the landscape and is the largest radio telescope with a full aperture in the world.

6. Effelsberg Radio Telescope

The large parabolic antenna with a periphery of 100 measures is one of the biggest telescopes in the world. It is 360- a degree gyration and takes 12 twinkles.

7. Medicine Radio Telescope

Italy has a parabolic antenna of 32 meters which is also used in interferometric devices and different arms antennas perpendicular to each other.

8. Sardinia Radio Telescope

11. Square Kilometer Array Radio Telescope

Currently, the study uses a network of thousands of antennas installed in Australia and South Africa. By combining the recorded signals, it is possible to obtain a collection area equivalent to one of the 1 km square parabolic antennas.

12. Voyager 1

Voyager is space solar-based interstellar in the space in the solar system launched by NADA in 1977 and it has a Max speed: of 61,500 km/h along with a decahedral bus, 47cm in height and 1.78 m across flat. 3.66-meter diameter with the parabolic high antenna placed top bus.

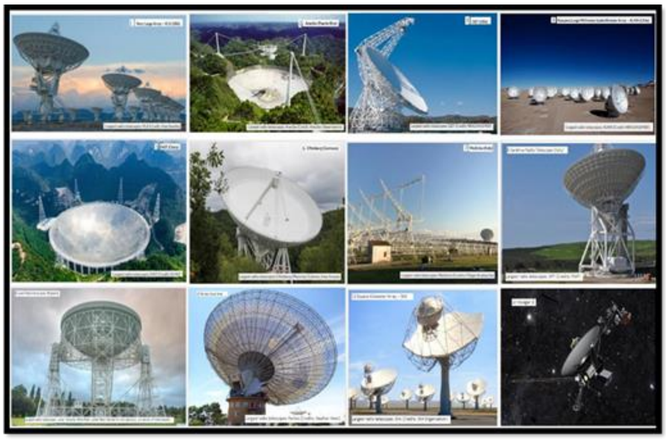
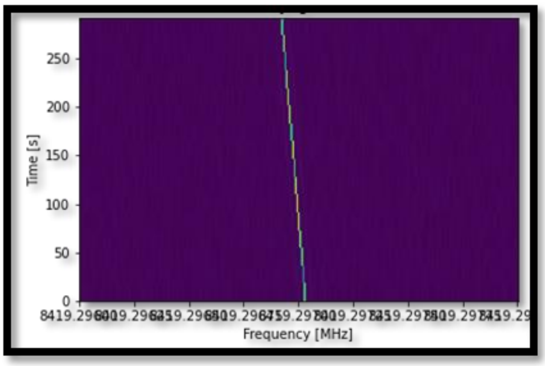
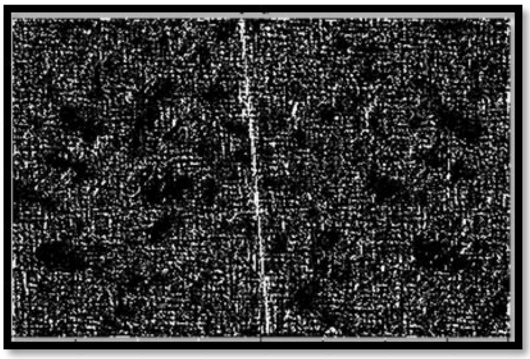


Fig 1: List of exiting telescopes on earth for collecting data by using an antenna with range frequents depending on the capacity of the station location as per the region [2].

Fast radio bursts are powerful energy in the form of radio waves, which have the power to release energy in a few thousandths of a second as compared to the object in the solar system [8]. This situation is most evident in a prism. When white light enters one side, it is divided into seven colors due to scattering. Figure given below demonstrates fast radio busts are present in the data set by considering the theory from Lorimer burst in 2009[9].





(a) (b)

Fig 2: A example of FRB detected by ML and CNN in the data set(a) and the “Lorimer burst”event(b) in our data set [9].

When a waves from an FRB pass through the interstellar and intergalactic medium, they experience dispersion. Lower-frequency components of the radio wave are delayed more than higher-frequency components. As a result, the signal spreads out in time, and what was once a sharp, brief burst becomes spread out over a range of frequencies. This dispersion effect is quantified using a parameter called the dispersion measure (DM)[10]. which provides information about the density of electrons along the path the radio waves travelled. By measuring the dispersion of an FRB and knowing the properties of the interstellar and intergalactic medium, astronomers can estimate the distance the radio waves have travelled and gain insights into the conditions and characteristics of the medium they passed through. This information can be crucial in tracing the origins of FRBs and studying the environments they encounter on their cosmic journey [11]. This propagation is the result of an interstellar environment that causes a time delay. This provides a "swooping curve" in the radio spectrum program instead of aircraft waves. If we multiply the pulses to increase the SNR, we assume that the pulses arrive at the same time. So we need to correct the propagation by shifting each channel with a certain time delay concerning its frequency channel. We indexed the frequency column in the spectrogram. We then divide it between the time delay and the original data and switch positions [12]. DM is the integral signal path of the interstellar medium. What we can do is force the amount of DM by performing multiple DM tests, where we get the highest SNR created in the dispersion with that DM test [13].

2. Dataset

Fast radio busts data is collected into file called filter bank and extension is (. fil). Most data in this file is binary or time search is recorded using an analog filter system for further detection of FRBs. It has many time adjustments and frequency varies with blast data collected. AFB data are furthermore available in SCAMP format (a format that predates. fil standard). Filter bank providers are stored data that has FRBs in archive files in profits format or in ASCII files format, it depends on provided parameters and requirement. Additional text files are also given with information in file formats called metadata or raw files [14].

A hierarchical Data Format is a set of file system formats used to store complex and large data sets. Version 5 of HDF, commonly known as HDF5, supports the storage of many different systems for the same data. It also supports group formation, acting as data containers or other groups (HDF Group, 2006) [15]. The HDF5 format is an excellent storage container for modified FRB and similar NumPy rear members. The file contains two groups named 'FRB' and 'BAK'. The FRB team retains the modified FRB while the BAK group retains the matching background. During the modeling process, the HDF5 file can be read [8].

3. System Architecture

Machine learning and deep learning model has different approaches and we have selected the best classification model for prediction after much testing on methodology /algorithms to show the best fit model below the proposed system architecture work apathetically from start to end of the prediction result.

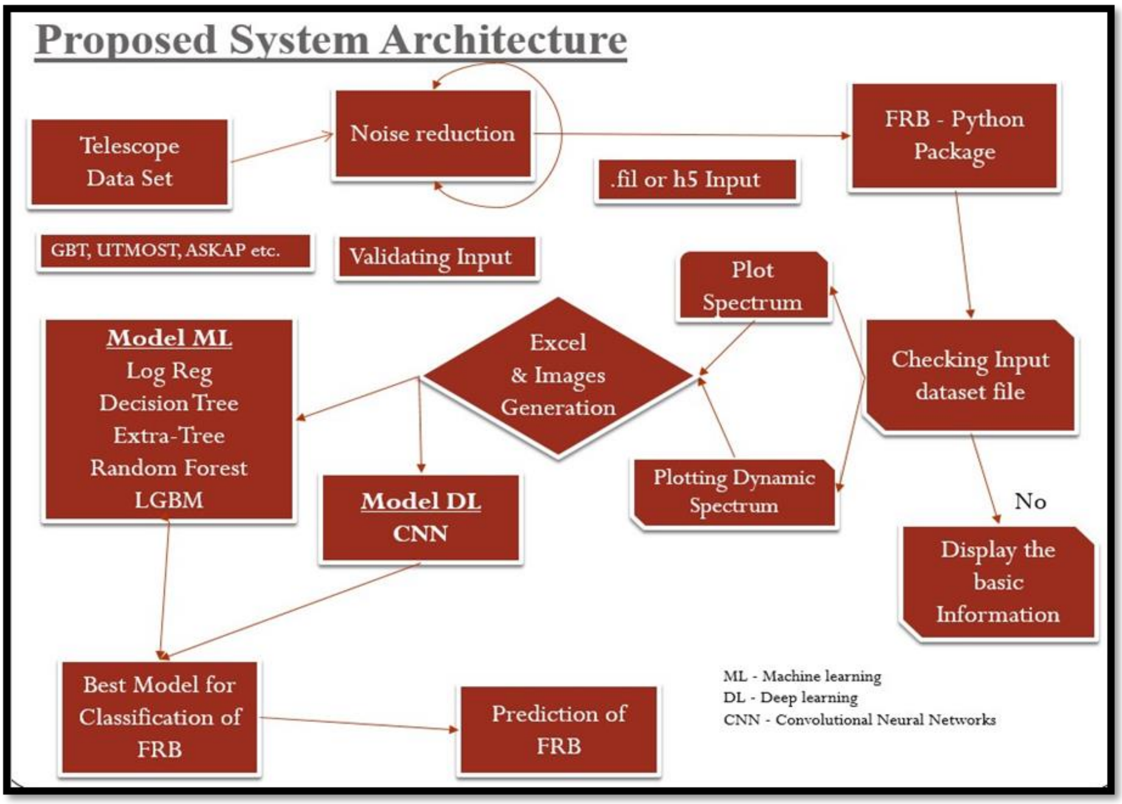


Fig 3: System architecture overview for a complete demonstration of FRB detection and classification.

The proposed system architecture, provides the overall flow of the complete system. As we know that data were collected at telescope station as per the base telescope setup, which is in the binary format which is collected or proceed by GPU. The proposed pipeline with the help of python package further reading the data and selecting feature for proceeding it for further expansion. If any feature not available, then it will be showing base details from which we have to select specific feature. Deep learning further reduces that problem it converts the signal into the spectrum. As we will be having a spectrum range then we can convert it into smaller images and track excel of all images data sets. Once we have all datasets ready then we will be following the below architecture for detecting FRB.

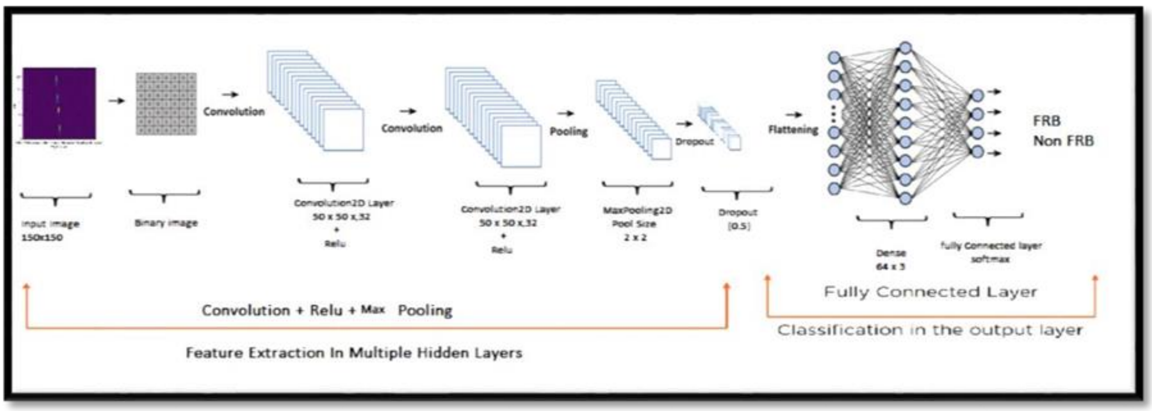


Fig 4: CNN Algorithm Architecture for detecting FRB from the dataset after processing signal.

Deep learning approaches are best-practices for image classification, and it is effectively achieved with Convolutional Neural Networks [16, 22] along with different methods.

In the CNN feature extraction on input images have multiple layers of convolution 2D layer with 50x50x32,

CNN Algorithm plays a vital role in the system for detection of various classes from the images data set [12,13,14]. We are applying Data augmentation as a technique to artificially create new training data from existing training data. Mainly it retrieves images and their classes for training and validation sets further Keras ImageDataGenerator ( ) function/class allows to perform image augmentation on data [17]. This data is further used for training of the model. Finally, ready for loading all the images with their classes/labels (classes/labels will be derived from the name of sub-directories automatically). We don't need to explicitly mention class names in method arguments [26, 27].

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 50, 50, 32)        896

 activation (Activation)     (None, 50, 50, 32)        0

 max_pooling2d (MaxPooling2D  (None, 25, 25, 32)       0
 )

 conv2d_1 (Conv2D)           (None, 8, 8, 32)          9248

 activation_1 (Activation)   (None, 8, 8, 32)          0

 max_pooling2d_1 (MaxPooling  (None, 4, 4, 32)         0
 2D)

 flatten (Flatten)           (None, 512)               0

 dense (Dense)               (None, 64)                32832

 activation_2 (Activation)   (None, 64)                0

 dropout (Dropout)           (None, 64)                0

 dense_1 (Dense)             (None, 3)                 195

 activation_3 (Activation)   (None, 3)                 0

=================================================================
Total params: 43,171
Trainable params: 43,171
Non-trainable params: 0
```

Fig 5: Keras's Sequential Model with multiple hidden layers as per the above CNN Algorithm Architecturefor detecting FRB

Models can be defined either with the Sequential API or the Functional API but we selected the sequential model API as it is the simplest and it involves defining a Sequential class and it is flexible to add layers to the model one by one in a linear manner, from input to output [18].

The system is required to create a sequential model and add layers one at a time until the network architecture shows satisfied results with the CNN algorithm [25]. We introduced an auto-detection model layer in the CNN model to get good results. In case of disappointed results from the model add new layers to the model and training new model for four iterators. Otherwise it will start removing layers until the first layer of the model [19, 24].

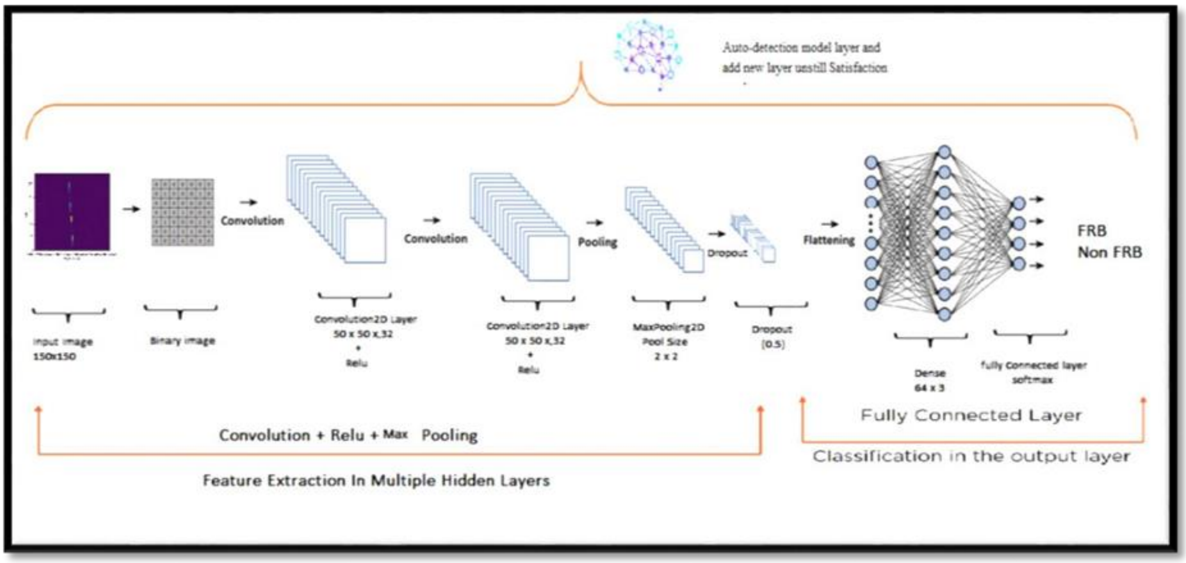


Fig 6: Algorithms along with CNN to add hidden layers for exiting model and training again

Further in parallels, different best fit algorithms for classification datasets like "LogReg, Decision Tree, Extra- Tree, Random Forest, and LGBM" from the machine learning model has been executed to get a satisfaction model, result that is compared with the deep learning model [20, 21, 22, 23].

4. Implementation Details

Overall, deep learning – CNN model implantation mentioned below and code will be available on GitHub https://github.com/MITWPU2022/Project-SY under an open-source. Where the new request for enhancement of code along with new changes will be uploaded.

The layers of models are given below in fig 7., every model is having the different layers which are giving the best result as per the open data set tested along with different methods.

Visualization of Layers Ouptut

```
model_layers = [ layer.name for layer in model.layers]
print('layer name : ',model_layers)
print('layer name : ',model_layers[2])

layer name :  ['conv2d', 'activation', 'max_pooling2d', 'conv2d_1', 'activation_1', 'max_pooling2d_1', 'flatten', 'dense', 'activation_2', 'dropout', 'dense_1', 'activation_3']
layer name :  max_pooling2d
```

Fig 7: Visualization of layers with partial code

The first convolution layer is used for extracting features from the input dataset of images. It creates pixelsfor each image by deep learning of images with small squares. Further it will be represented in mathematical such as an image matrix and a filter or kernel. Let's review the single convolution filter output with the first convolution features layer to have more clarity on the model. The convolution feature layers are available in the ranges "conv2d_features[0,:,:, 4]" and imshow( ) function help us to show the output of the image and display image as grayscale also function taken from matplotlib.

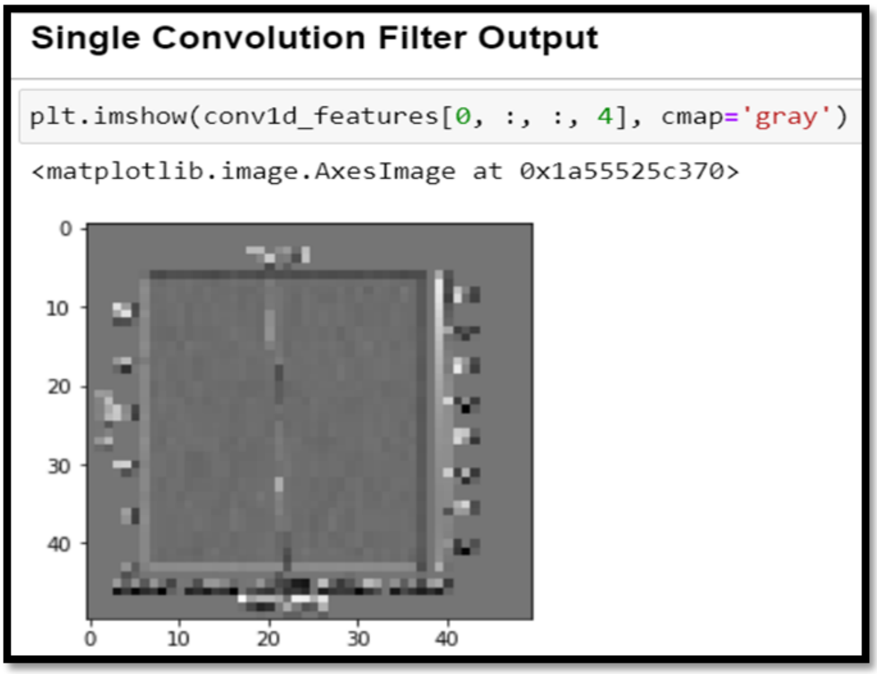


Fig 8: Signal convolution filter output

Convolution of an image has different filters which can perform operations for detection of edge, blur, and sharpen by applying filters and First convolution layer demonstrator available filters in the model and it is in the range of 32 to view a few images for the filters and it clearly shows that model has created different filters base of on the feature extraction from the model.

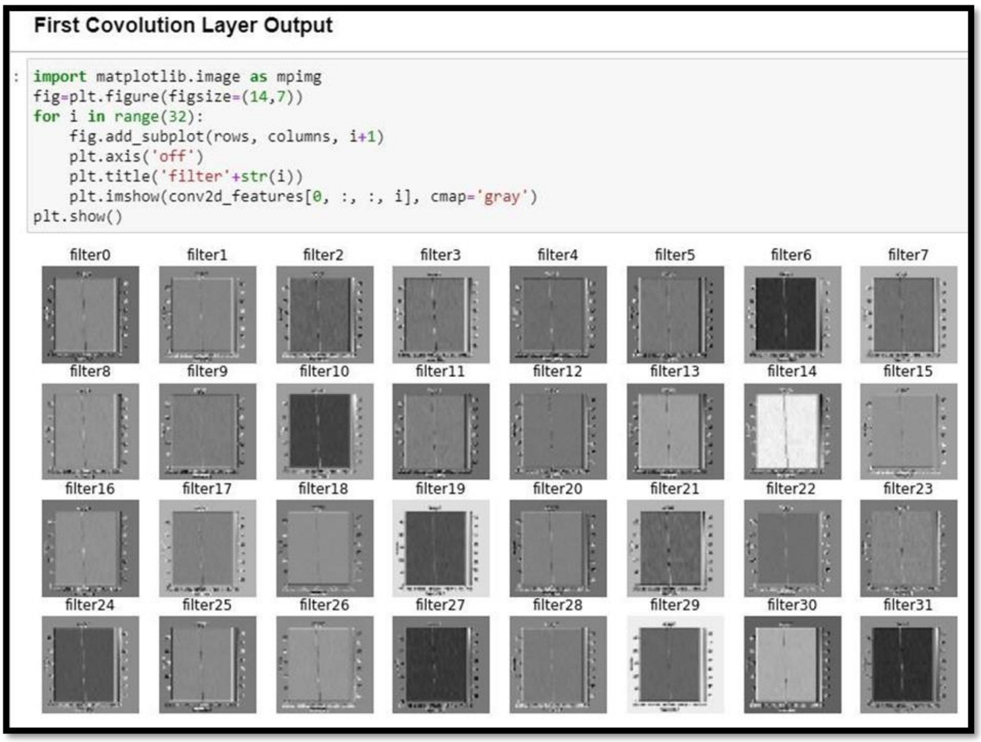


Fig 9: First convolution layers of 50 x 50 x 32 output side**.**

The model used to stride the number of pixels by 2 which means filters moved by 2 pixels for each image and Convocation 2d layer 1st has 50x50x32 side with activation function ReLU of side 50x50x32 along with max- pooling 25x 25x32, further first layer connected with the second layer of configuration as Convocation 2d layer 2nd has 8x8x32 side with activation function ReLU of side 8x8x32 along with max-pooling 4x 4x32.

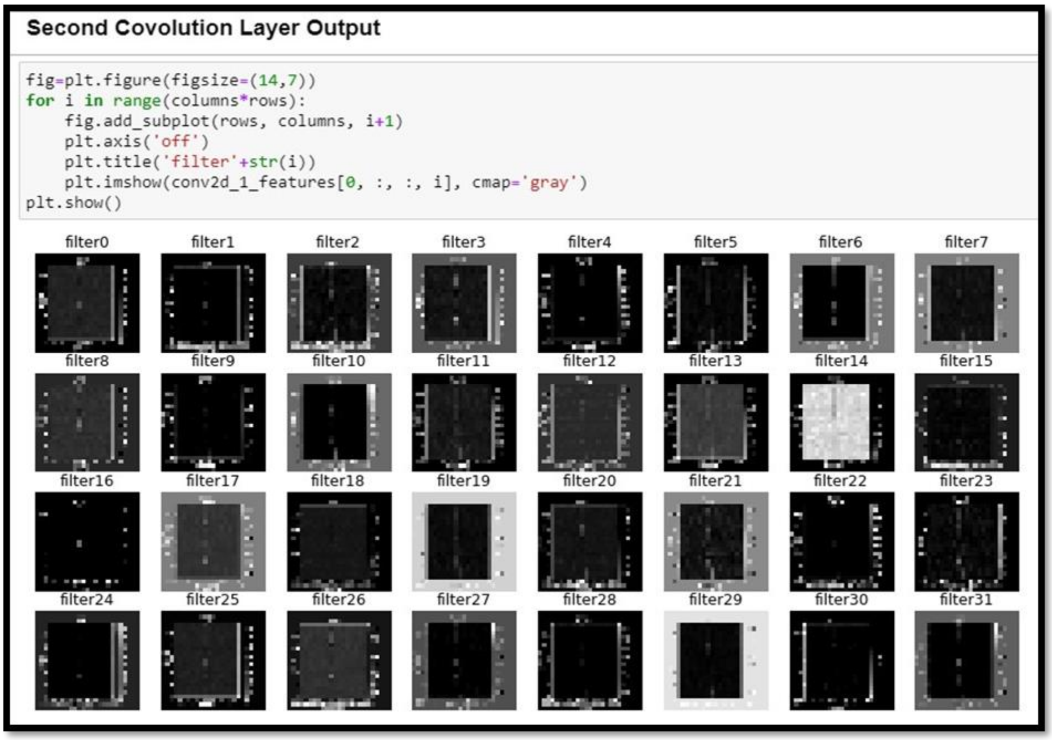


Fig 10: Second convolution layers of 8 x 8 x 32 output side.

Overall layers, ReLU as activation function to introduce non-linearity in our ConvNet and pooling Layers section used to reduce the number of parameters. When the images are too larges in dimension and max pool used purpose is the rectified element with feature map.

Furthermore, the dropout layer by 0.5 is done by randomly setting input units to zero with a frequency for each training time to prevent overfitting and make sure that scales are not to be zero in such a way that sums over all input unchanged. Finally, the fully connected layer used feed-forward networks after applying flattened andthen fed into the fully connected layer.

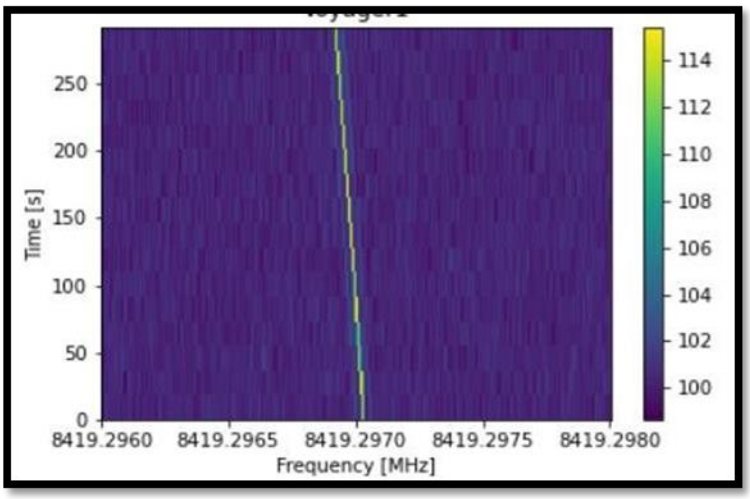


Fig 11: Output of classified as FRB images

Fig 11, is from the output of the classification after applying the softmax function in the fully connected network and tis used for multi-classification in the Logistic Regression model.

5. Result Discussion

Finally, Machine learning and deep learning have achieved the expected result and data classified successfully with very good accuracy. Some optimal algorithms are demonstrated in this research article to achieve the result. These results will help for further analysis of the cosmos and for identifying FRBs. The algorithms used were CNN, LogReg, Decision Tree, Extra-Tree, Random Forest, and LGBM.

The newly created pipeline is equipped for handling different file formats and also provide spectrum analysis of overall frequency. This pipeline helps to understand the overall spectrum. This pipeline divides the overall spectrum into image data sets, which is having a frequency infraction. The algorithm will start initial point to the endpoint and creating thousands of images from the available data sets in such a way that it will be having every point(parameter) of all the signals.

Fig 12: Showing output result after classification in different folders along with excel.

After application of machine learning and deep learning algorithm, the model created a folder structure of FRB and non-FRB images, labeled data, shown in fig 12 and also excel file is generated with the complete track of images.

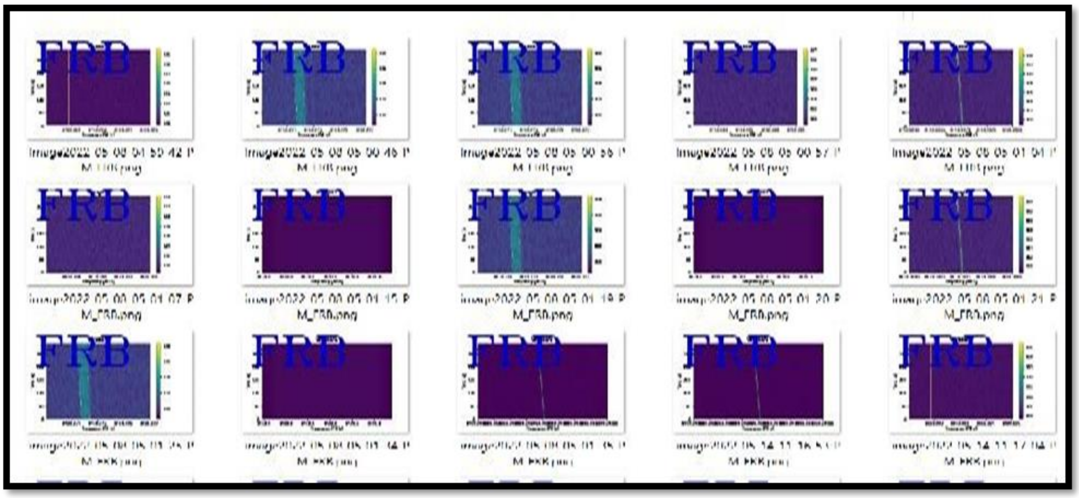


Fig 13: Detection of FRB in the dataset with CNN model and model has accurately classified the images ineach folder

Let’s understand the FRB classification images as shown in Fig 13, as per the FRB definition and research carried out, the above images are the type of FRB since its clear visible signal in the images along with model labeling given to each image. The accuracy we received is 98.3%.

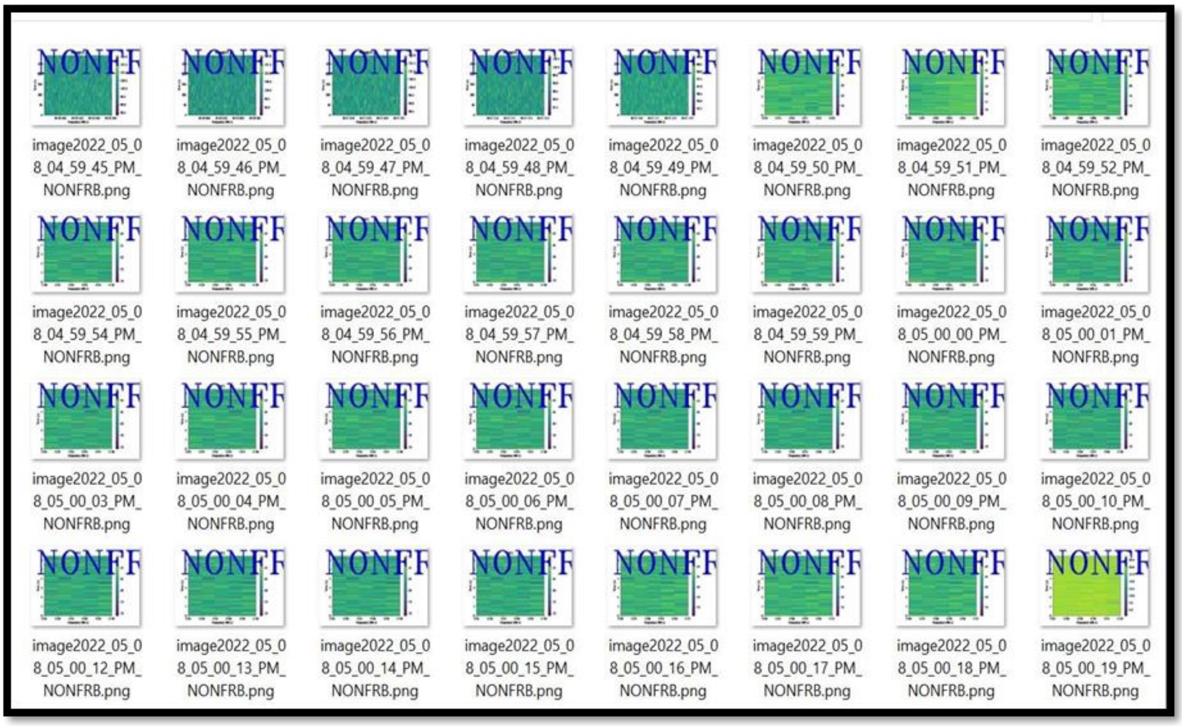


Fig 14: Detection of NON-FRB images in the dataset with CNN model and model has accurately classifiedthe images in each folder

This classification has one more folder as a result, we called it Non-FRB, where the images has a similar pattern with no signal spectrum hence its Non-FRB images. Which do not qualify for FRB and we can ignore this images.

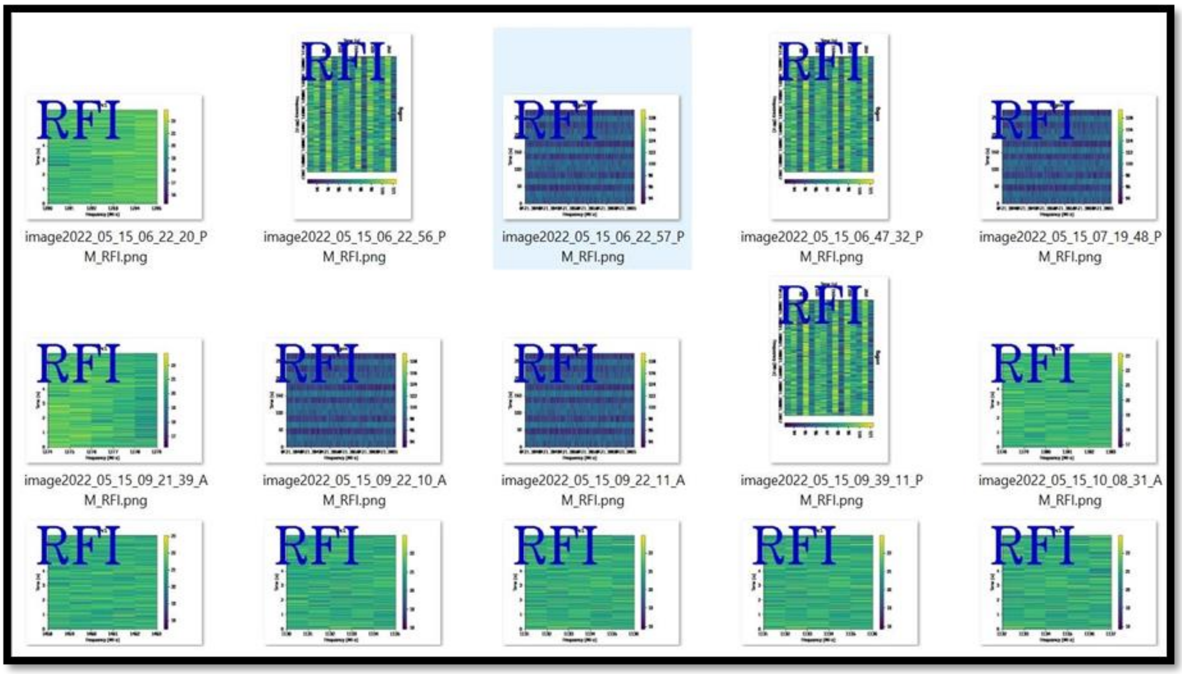


Fig 15: Detection of a non-FRB signals, with CNN model and model has accurately classified the images in each folder.

On the other hand, we received some unknown or non-identified images, which required definition and understanding according to the behavior of the signal.

Image File	Prediction
l\fig2_2022_04_28_06_13_57_AM.png	NONFRB
l\fig2_2022_04_28_06_13_58_AM.png	NONFRB
l\fig2_2022_04_28_07_06_48_AM.png	FRB
l\fig2_2022_04_28_07_08_12_AM.png	FRB
l\fig2_2022_04_28_07_12_00_AM.png	FRB
l\fig2_2022_04_28_07_12_38_AM.png	FRB
l\fig2_2022_04_29_12_35_11_PM.png	FRB
l\fig2_2022_04_29_12_35_12_PM.png	NONFRB
l\fig2_2022_04_29_12_35_13_PM.png	NONFRB
l\fig2_2022_04_29_12_35_14_PM.png	NONFRB
l\fig2_2022_04_29_12_35_15_PM.png	NONFRB
l\fig2_2022_04_29_12_35_16_PM.png	NONFRB
l\fig2_2022_04_29_12_35_17_PM.png	NONFRB
l\fig2_2022_04_29_12_35_18_PM.png	NONFRB
l\fig2_2022_04_29_12_35_19_PM.png	NONFRB
l\fig2_2022_04_29_12_35_20_PM.png	NONFRB
l\fig2_2022_04_29_12_35_21_PM.png	NONFRB
l\fig2_2022_04_29_12_35_22_PM.png	NONFRB
l\fig2_2022_04_29_12_35_23_PM.png	NONFRB
l\fig2_2022_04_29_12_35_24_PM.png	NONFRB
l\fig2_2022_04_29_12_35_25_PM.png	NONFRB

Fig 16: Based on the CNN model prediction, all images have been classified in excel.

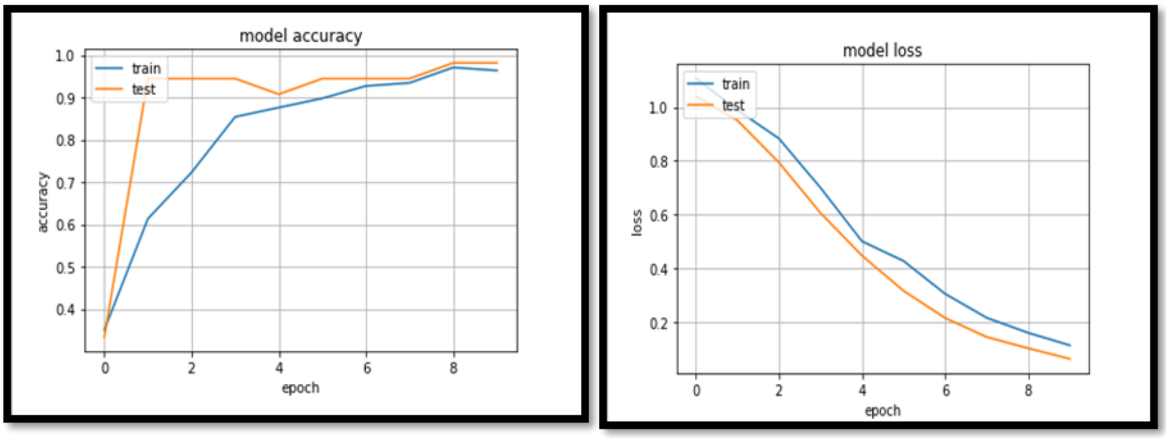


Fig 17: Model accuracy and model loss by using a line chart over the epoch. Train data marked by orange color blue color used for test data

The loss rate suggests how the model behaves inadequately or positively after each set of adjustments. A fine-scale is used to measure the performance of the algorithm descriptively. Most of the time we see pleasure increase with the loss. but this is not always the case. Pleasure and loss have different meanings and measure different results. They usually seem equally similar but there is no good relation between the two approaches.

Machine learning plays a very critical role in the system since it is considered for model review on the basis of performance as the data set grows hugs amount then deep learning could be used only but to demonstrate the performance of the system below fig 17 shows overall accuracy for each model and logistic regression is highly be considered if the data set are in the smaller size and model is the best fit for classification of the data from respective accurately and balanced for data set.

5.1 Performance

The model has been tested on different datasets and source files to get the best result of classification. Fig 18 is showing few lists of algorithms tested for the accurate result.

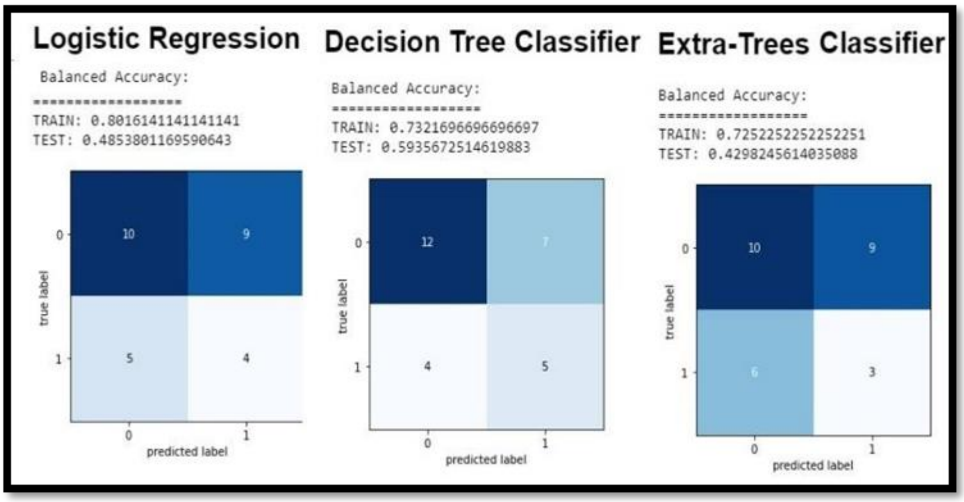


Fig 18: Comparison of machine learning models: Logistic Regression, Decision Tree and Extra-Tree

Logistic regression is the best when we want to check independent variables such as true/false, yes/no, and so on which is forced on binary output. Above models provide training accuracy between 0.80 to 0.90, and testing accuracy ranges between 0.48 to 0.85.

Similarly, classification and regression data can be handled by decision tree the training accuracy is 0.73 and the testing accuracy is 0.59 for same data sets which is less as compared with logistic regression, but better than an extra-tree, training accuracy for Extra-Tree is 0.72 and testing accuracy is 0.42.

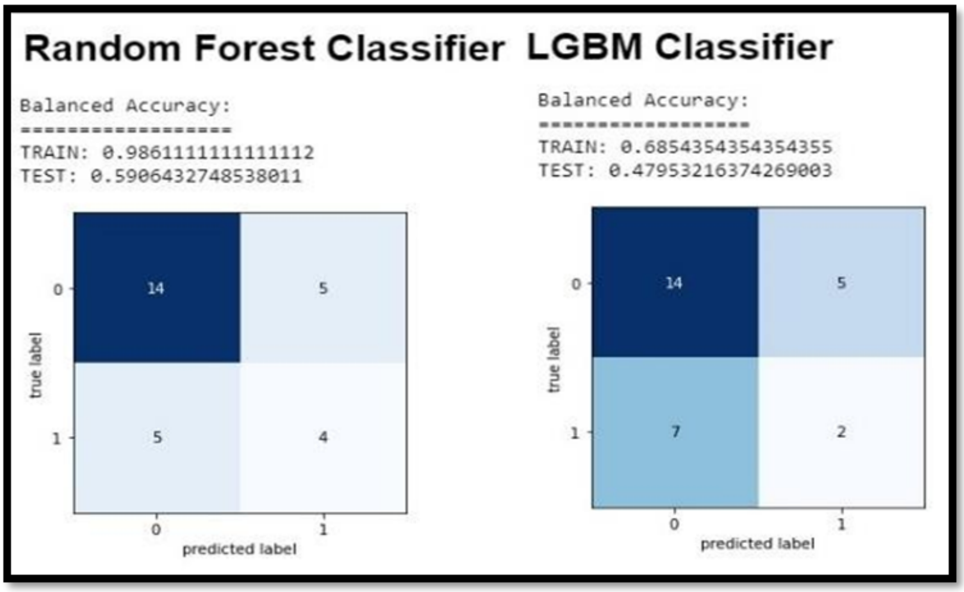


Fig 19: Comparative accuracy of Machine Learning models: Random Forest and LGBM

Logistic regression is one of the binary output models and the best fit for our classification if checked the training accuracy is 0.98 and the testing accuracy is 0.59 which is highest as compared with another model butless than the CNN model. Finally, we can conclude that CNN model has the best for accuracy. The LGBM model has very less accuracy as compared with any model so it is not recommend for considering the results and accuracy for classification.

Here is the confusion matrix for the CNN model along with the performance of classification gives best results. Where values are true for known label 0 are FRB and 1 for Non-FRB. Training accuracy of the CNN model which is 99.27 % along with validation of 98.15%. Model loss over epoch has been showed in fig 17.

	Model	train_balanced	test_balanced
0	CNN	0.99270	0.98148
2	Decision Tree	0.73217	0.59357
4	Random Forest	0.98611	0.59064
1	Logistic Regression	0.80161	0.48538
5	LGBM	0.68544	0.47953
3	Extra-Trees	0.72523	0.42982

Fig 20: Machining learning vs deep learning final result as per the train and test balanced of the data

CNN Model Confusion Matrix

```
Confusion matrix :
 [[27 19]
 [32 14]]
Outcome values :
 27 19 32 14
Classification report :
              precision    recall  f1-score   support

           0       0.30      0.59      0.39        46
           1       0.30      0.30      0.30        46

   micro avg       0.30      0.45      0.36        92
   macro avg       0.30      0.45      0.35        92
weighted avg       0.30      0.45      0.35        92

Training Accuracy  : 99.27%     Training loss  : 0.050098
Validation Accuracy: 98.15%     Validation loss: 0.062864
```

Fig 21: CNN model Confusion Matric and model training accuracy/loss result

Here, is the model list with six algorithms, which is sorted over train balanced data in such a way that we can understand easily which is the better model. These models were used for classification and dynamic model selection method. After the results comparison, the CNN model as the best model for classification. All the implementation and the python packages are available on GitHub, with continuous further modification for better result. As per the results received provided in Fig 22, it is observed that CNN model performance is high well as compared to another model of ML algorithms.

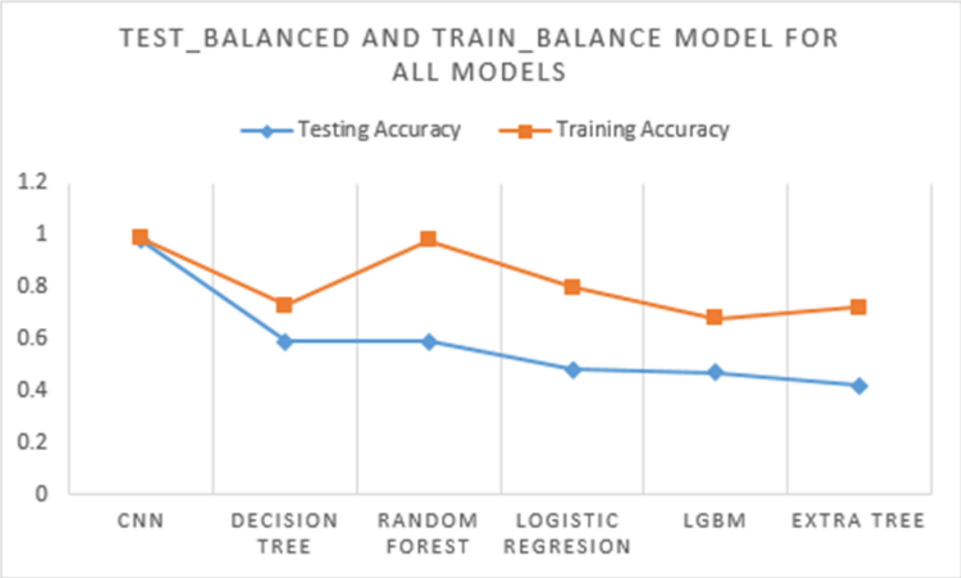


Fig 22: Result of CNN Test balanced Model VS ML Test balanced model

6. Conclusion

This research article, presented the, various machine learning model for classification of FRBs and Non_FRBs. We identified the most effective model from machine learning and deep learning. Log Reg, Decision Tree, Extra-Tree, Random Forest, LGBM and Convolutional Neural Networks models were chosen for comparison.

Fast radio burst data were simulated after precise knowledge of their properties and Gaussianrandom noise was used for the high-frequency interference.

Although CNN model performed faster in sample data, performance was not optimal. The other two models performed well, but the feature extraction effort slowed them down during the prediction. Hence, it concludedthat convolutional neural networks are best suited for use in large radio telescopes such as square kilometers.

The architecture of CCN is capable of producing an accuracy of 98% on the validation dataset, which is pretty good. It is possible to achieve more accuracy of 99% on this dataset, using a deep learning network and fine-tuning network parameters for training. The study was conducted on an existing reference paper and most of the papers listed in the below reference section.

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