# SETI (Search for Extra Terrestrial Intelligence) SIGNAL CLASIFICATION USING MACHINE LEARNING

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**Abstract -** In this paper, a literature review on SETI signal spectrogram image classification is presented. Since there has been an abundance of astronomical data, automation seems to be the easier solution for classification and this brings in machine learning into the picture. In this paper, we have discussed both traditional methods and automated methods and also made an analysis of which algorithm comparatively has better performance

**Keywords:** SETI, Spectrogram, Convolutional Neural Network, signal classification.

## 1. INTRODUCTION

### 1.1 Theoretical Background

The goal of SETI is to understand and explore the nature and origin of life in this universe and how intelligence evolved.

The University of Berkeley, Berkley SETI Research Center created a project named "Breakthrough Listen" which is stated as one of the most elaborate search for alien life and communication. The radio signal data from space is gathered by Parkes Observatory in New South Wales and Green Bank Observatory in West Virginia and the optical data is collected by Automated Planet finder located in California

This project has the software and hardware for signal collection, money, time and the expert to run. The only sticking point is the data. Even after compromising on the raw data's time or frequency resolution, Breakthrough Listen is archiving 500GB and data every hour[1]

### 1.2 Motivation

During 2017, SETI conducted a machine learning competition where simulated datasets were given to the competitors and a blinded test set. The team that won the competition, obtained an accuracy of about 95 percent. They used a Convolutional Neural Network and the aim was to classify signals by going beyond the traditional methods for signal analysis. The goal was to convert the signal classification task into image classification by converting them into spectrograms. [1]

SETI has now started to release datasets for machine learning for the purpose of automated classification. Even though the dataset that is released is small, it is still sufficient for deep learning analysis. The motivation of this project is to apply machine learning techniques to classify images with decent accuracy.

### 1.3 Aim of the proposed work

To classify spectrogram signals using machine learning techniques namely Convolutional Neural Network and Image processing techniques.

### 1.4 Objective(s) of the proposed work

- Develop an algorithm to classify signals of the datasets.
- Stimulate the data to create new datasets with different types of signal.

## 2. LITERATURE SURVEY

### 2.1 Survey of the Existing Models/Work

Traditional classification method:

An advanced method for classifying bird species from the audio signals is presented in [1]. The authors use features like syllable textures in audio spectrograms, which has a considerable discerning effect amongst the bird classes. The spectrogram is computed from the audio. The syllables from the spectrogram is extracted using an enhanced syllable extraction technique. Then, GLCM –Gray Level Co-occurrence Matrix is computed using the texture features and are further used for classification.

A system to monitor food intake by using a microphone in throat is discussed in [3]. The aim of the work is to classify the food being intaken using the spectrogram analysis. The food being classified are sandwich chewing, sandwich swallows, water swallows and none. The obtained F-score value was 0.84.

A spectrogram based classification technique is used for classifying music genre is detailed in [4]. The proposed technique combines the Singular Value Decomposition (SVD)'s dimensionality reduction power with the Wavelet Package Decomposition (WPD)'s multi resolution analysis so the the desired features can be extracted. The accuracy of the new method is evaluated using GTZAN and ISMIR datasets.

A novel method is examined in [5], where a model to classify movements using accelerated spectrogram which is used in combination with dynamic time warping method is discussed. The method firstly collects data using an accelerated sensor which is embedded in a mobile device. Then it filters coordinate information. Then, the data is modified to a spectrogram and the RGB values of the spectrogram are used in classifying the movements. A DTW algorithm is used in the classifying these changes. The model is evaluated by experimenting with 3 human movements namely walking, moving upstairs and downstairs.

A system is designed to classify basic types of digital modulation signals such as Phase Shift-Keying (PSK), Frequency Shift-Keying (FSK) and Amplitude Shift-Keying (ASK) is discussed in [6]. The spectrogram time frequency analysis for analysis and a rule based classifier is used for classification. The instantaneous frequency is removed from the frequency-time presentation and then used to estimate the parameters of the modulation type. This data is fed as input to the rule based classifier. The accuracy of the system is evaluated by adding Gaussian white noise. The accuracy obtained is around ninety percent

A biological image based classification technique to classify creatures based on their sounds is proposed in [7]. The method involves spectrogram image extraction using relative spectral transform-perceptual linear prediction, spectrogram routing using Hilbert curve, feature matching using cosine similarity and 1-D spectrogram classification using Gaussian mixture model.

A novel method is proposed in [8] to extract features from modulation spectrogram and or classification of phonemes in Gujarati. The 2-D modulation spectrogram is reduced to a 1-D feature vector , which is smaller than the original. The language was manually classified into thirty one classes.

Then Support Vector Machines (SVM) is used to classify the phonemes. The accuracy of the classification is 95% which is better compared to the Mel frequency cepstral coefficients (MFCC), which yields 92.74 % classification accuracy.

A new method is proposed in [9] which uses a time frequency approach for spectrogram image processing technique to analyze EEG signals. Texture Features are extracted using Gray Level Co-occurrence Matrix (GLCM) and then further dimentionality reduction is done using Principal components analysis (PCA). Then K nearest neighbor is used to classify EEG spectrogram and the accuracy was shown to be 70 percent for EEG spectrograms.

A novel method of classification for bird song syllables was proposed in [10] where multitaper spectrogram is decomposed to singular vectors, which is used as feature vectors. This method is

particularly useful for signals that contain several components and have variations in the frequency as well as time fields. The method is compared with several other methods and the experiments show that there is a string similar component in all signals and when the weak components differ, then for sch cases, singular vector decompositions seems useful.
A method for feature extraction for classifying music and speech audio is developed in [11]. A novel technique which combines signal and image processing technique is proposed. The audio is first segmented and converted to a spectrogram image and then image preprocessing techniques are applied to detect necessary features . Finally, 2-D fourier transform is applied to transform these extracted features to find out the energy of the signal at particular frequencies. A support vector machine is used for classification. Results show that the proposed method achieves good accuracy as expected.

Automated classification:

A method is proposed in [12], where signal data from Allen telescope array is used to find extraterrestrial signals from outer space. Representation learning, which uses different types of self-supervised and auto-encoding deep learning, are used to identify and categorize various forms of Radio Frequency Interference(RFI).The excision of RFI allows the remaining signals to be explored to find anomalies worthy of follow-up measurements. The work is corroborated with Search for Extra Terrestrial Intelligence Institution and it focuses on dimensionality reduction and clustering for RFI categorization, automated representation learning, Fast fourier transform for feature engineering and density equalization to do unsupervised learning.

A proposal for Deep Convolutional Neural Networks for the Generation of High Fidelity Images from Radio Interferometer Visibility Data is discussed in [13]. In this paper, the authors argue that a deep convolutional neural network (CNN) can be a highly (computationally) effective approach to radio interferometer image generation starting from raw visibilities and producing high fidelity, cleaned (deconvolved) images as an output. They consider the linear and nonlinear operations performed in image generation and how they have analogs in a standard CNN. They also discuss the potential computational cost savings that might be had by replacing our complicated image processing pipelines with neural networks.

### 2.2 Summary/Gaps identified in the Survey

Although spectrogram classification has been done previously, using machine learning, only a handful papers have been published and for the undertaken dataset, no machine learning papers have been published yet. So there is a dearth of using machine learning for spectrogram classification.

## 3. PROPOSED SYSTEM REQUIREMENT ANALYSIS AND DESIGN:

Requirements analysis encompasses those tasks that go into determining the needs or conditions to meet for a new or altered product or project, taking account of the possibly conflicting requirements of the various stakeholders, analyzing, documenting, validating and managing software or system requirements.

Requirements analysis is critical to the success or failure of a systems or software project. The requirements should be documented, actionable, measurable, testable, traceable, related to identified business needs or opportunities, and defined to a level of detail sufficient for system design.

### 3.1 Requirement Analysis

#### 3.1.1 Functional Requirements

##### 3.1.1.1 Product perspective

Execution time i.e. speed is one of the crucial factors for the proposed system. Signals should be processed quickly so that quick action can be taken to trace that signal.

### 3.1.1.2 Product Features

The system classifies the signal accurately.
The system classifies the signal within acceptable time limit
The system will not consume more system resource
The system will be functioning all time without any break.

### 3.1.1.3 User characteristics

The user is not required to know any technical details. Just looking at the output and figuring out what class the signal belongs is enough from the user end.

### 3.1.1.4 Assumption,Dependencies & Constraints

#### Assumption

The system assumes that a GPU(Graphics Processing Unit) is installed in the system. Also,t he system requires keras python library and keras works only on 64 bit system. Matlab is also a pre-requisite.
Another assumption made is that the system works perfectly and does not malfunction.

#### Dependencies

The system is divided into two parts. The output of the first part determines whether the second part is required to be executed. The first part classifies one among the seven output classes(one vs all classification). If it classifies accordingly, second part need not be executed as the output class is already known. If not, then the second part is to be executed to know the class.

#### Constraints

The system can run only on 64 bit system.

### 3.1.1.5 Domain Requirements

The system requires Python 3 or above and Matlab.

### 3.1.1.6 User Requirements and Product Specific System Requirements

The user expects the system to work with as much accuracy as possible and also should not exhaust memory space and execute within the time limit.
The system should alert the user when the required type of signal is detected.

### 3.1.2 Non functional Requirement

The system should be easily accessible to anyone who desires to use it.
The system should be compliable to user demands. The recovery of system from a disaster should be smooth. The efficiency of power consumption should be optimal.
The system should be extensible to be able to run in different platforms and different operating systems. The system should be resistant to faults .i.e. exception handling should be incorporated in the system. The system should be easy to maintain. The access to the system should be private only to required persons and security locks like password protection should be enabled.
The system should be portable to all platforms. The system must be reliable to the maximum extent to produce correct output. The response time should be less.
The robustness of the system should be such that it is not often prone to system errors.
The system should be stable and must not produce the different output at different times.
The testability of the system should be easy to facilitate easy testing.

### 3.1.3 Engineering Standard Requirements

The system should not cost more as there is no primary investment in any form and thus the returns should be cheap. The system should not cause harm to environment in any form like pollution or contamination. The dataset required should be acquired from a spectrometer that is not polluting to the environment. The system should not be accessible to all persons and should be password protected for security purposes. Any misuse and leak of information can cause unwanted problems. The system should not be biased towards any political needs i.e. no compromise in algorithm like biased training or testing due to political pressure. The system should not store or send any data without user's notification. Also unwanted leakage of data in any form from memory should be prevented. The system should be aimed for sustainable long term use and thus should incorporate elasticity in the algorithm. The system must not work on illegally obtained data and should not do anything illegal like stealing system information, sending hidden emails etc. The system should be easy to inspect in the sense that all codes should be visible and nothing should be hidden from the tester.

### 3.1.4 System Requirements

#### 3.1.4.1 Hardware Requirements

The system works only on 64 bit operating system with installed GPU(Graphics Processing Unit) and minimum 12GB RAM.

#### 3.1.4.2 Software Requirements

Python 3.6 or above and Matlab should be installed for the system to work.

## 4. DESIGN OF THE PROPOSED SYSTEM

The Design Overview is section to introduce and give a brief overview of the design. The System Architecture is a way to give the overall view of a system and to place it into context with external systems. This allows for the reader and user of the document to orient themselves to the design and see a summary before proceeding into the details of the design.

### 4.1 High Level Design

The architecture is pipe and filter model. In this pipe and filter style each component has a set of input streams and a set of output streams. A component reads streams of data on its input streams, processes the data and writes the resulting data on its output streams. Hence components are termed filters. The connectors of this style merge the streams together, i.e., they transmit outputs of one filter to inputs of another filter. Hence the connectors are termed pipes. Among the important invariants of the style is the condition that filters must be independent entities: in particular, they should not share state with other filters. Another important invariant is that filters do not know the identity of their upstream and downstream filters. Thus, filters may not identify the components on the ends of their pipes.

The software has basically 2 components, the first part does one vs all classification for one class. Based on the output of the first component, the second component is executed. If the output of first component is not a class, then the second component is executed. If not, the second component is not executed. It is shown in Figure 1.

## 5. IMPLEMENTATION

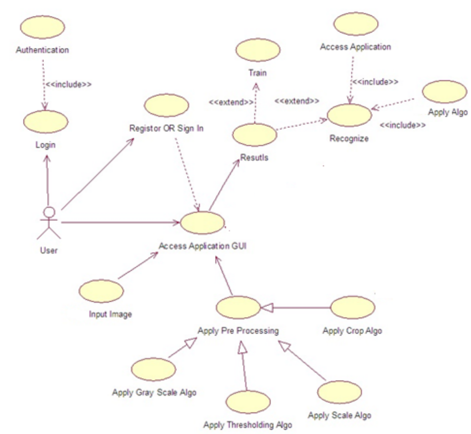


Fig1. Proposed model

## 6. RESULTS AND DISCUSSION

VGG16

Accuracy :0.142857(14.2857%)

| | PRECISION | RECALL | F1-SCORE | SUPPORT |
|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 100 |
| 1 | .14286 | 1 | 0.25 | 100 |
| 2 | 0 | 0 | 0 | 100 |
| 3 | 0 | 0 | 0 | 100 |
| 4 | 0 | 0 | 0 | 100 |
| 5 | 0 | 0 | 0 | 100 |
| 6 | 0 | 0 | 0 | 100 |
| Micro averag | 0.14286 | 0.14286 | 0.14286 | 700 |

| | | | | |
|---|---|---|---|---|
| e | | | | |
| Macro average | 0.02041 | 0.14286 | 0.03571 | 700 |
| Weighed average | 0.02041 | 0.14286 | 0.03571 | 700 |

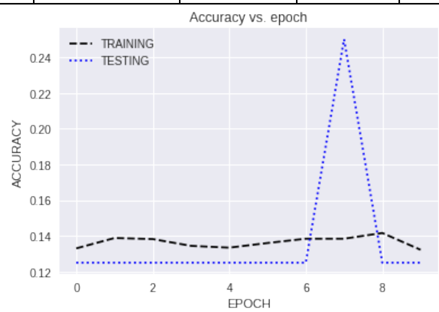


**Fig. 2.** Accuracy of VGG16

VGG 19

Accuracy :0.142857(14.2857%)

| | PRECISION | RECALL | F1-SCORE | SUPPORT |
|---|---|---|---|---|
| 0 | 0.14286 | 1 | 0.25 | 100 |
| 1 | 0 | 0 | 0 | 100 |
| 2 | 0 | 0 | 0 | 100 |
| 3 | 0 | 0 | 0 | 100 |
| 4 | 0 | 0 | 0 | 100 |
| 5 | 0 | 0 | 0 | 100 |
| 6 | 0 | 0 | 0 | 100 |
| Micro average | 0.14286 | 0.14286 | 0.14286 | 700 |
| Macro average | 0.02041 | 0.14286 | 0.03571 | 700 |
| Weighed average | 0.02041 | 0.14286 | 0.03571 | 700 |

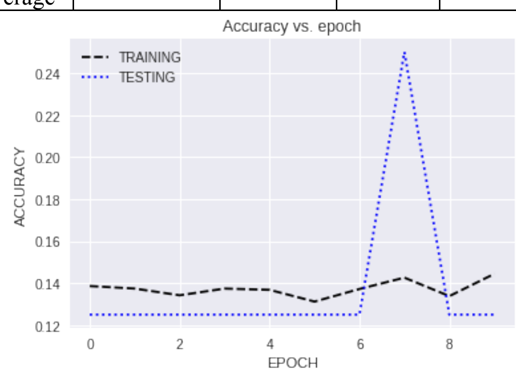


**Fig. 3.** Accuracy of VGG19

ALEXNET

Accuracy :0.142857(14.2857%)

| | PRECISION | RECALL | F1-SCORE | SUPPORT |
|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 100 |
| 1 | 0 | 0 | 0 | 100 |
| 2 | 0 | 0 | 0 | 100 |
| 3 | 0 | 0 | 0 | 100 |
| 4 | 0 | 0 | 0 | 100 |
| 5 | 0.14286 | 1 | 0.25 | 100 |
| 6 | 0 | 0 | 0 | 100 |
| Micro average | 0.14286 | 0.14286 | 0.14286 | 700 |
| Macro average | 0.02041 | 0.14286 | 0.03571 | 700 |
| Weighed average | 0.02041 | 0.14286 | 0.03571 | 700 |

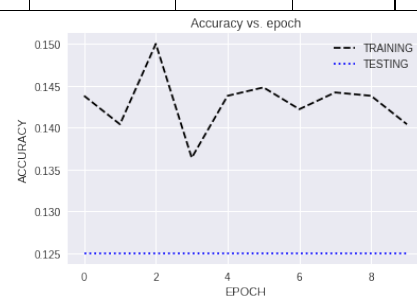


**Fig. 4.** Accuracy of Alexnet

GOOGLENET

Accuracy :0.142857(14.2857%)

| | PRECISION | RECALL | F1-SCORE | SUPPORT |
|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 100 |
| 1 | .0 | 0 | 0 | 100 |
| 2 | .14286 | 1 | 0.25 | 100 |
| 3 | 0 | 0 | 0 | 100 |
| 4 | 0 | 0 | 0 | 100 |
| 5 | 0 | 0 | 0 | 100 |
| 6 | 0 | 0 | 0 | 100 |

| | | | | |
|---|---|---|---|---|
| Micro average | 0.14286 | 0.14286 | 0.14286 | 700 |
| Macro average | 0.02041 | 0.14286 | 0.03571 | 700 |
| Weighed average | 0.02041 | 0.14286 | 0.03571 | 700 |

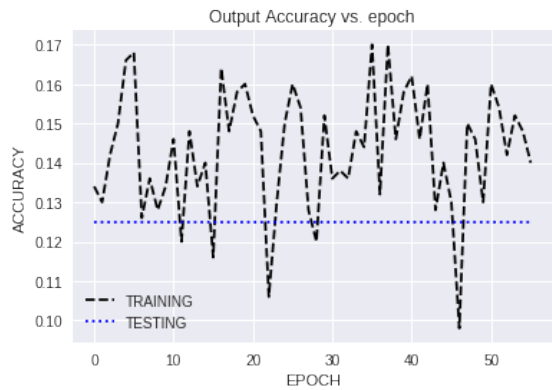


**Fig. 5.** Accuracy of Googlenet

INCEPTION NET

Accuracy :0.664285(6.4285%)

| | PRECISION | RECALL | F1-SCORE | SUPPORT |
|---|---|---|---|---|
| 0 | 0.73636 | 0.81 | .77153 | 100 |
| 1 | 0.69231 | 0.45000 | 0.54545 | 100 |
| 2 | 0.90385 | 0.47000 | 0.61842 | 100 |
| 3 | 0.68224 | 0.73 | 0.70531 | 100 |
| 4 | 0.91429 | 0.32 | 0.7407 | 100 |
| 5 | 0.51503 | 0.97 | 0.66897 | 100 |
| 6 | 0.63830 | 0.9 | 0.74689 | 100 |
| Micro average | 0.66429 | 0.66429 | 0.66429 | 700 |
| Macro average | 0.72541 | 0.66429 | 0.64722 | 700 |
| Weighed average | 0.72541 | 0.66429 | 0.64722 | 700 |

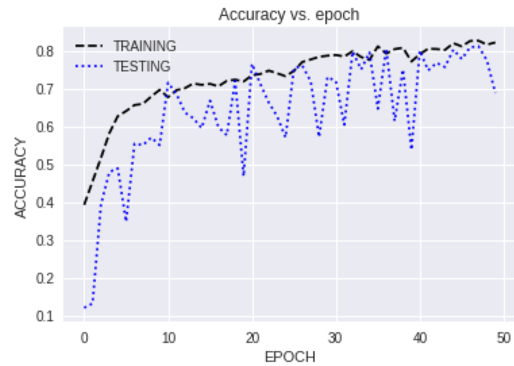


**Fig. 16.** Accuracy of Inception net

PROPOSED MODEL

Accuracy : 0.824285(82.4285%)

| | PRECISION | RECALL | F1-SCORE | SUPPORT |
|---|---|---|---|---|
| 0 | 0.83333 | 0.80000 | 0.81633 | 100 |
| 1 | 0.81982 | 0.91000 | 0.86256 | 100 |
| 2 | 0.89655 | 0.78000 | 0.83422 | 100 |
| 3 | 0.68644 | 0.81000 | 0.74312 | 100 |
| 4 | 0.96774 | 0.60000 | 0.74074 | 100 |
| 5 | 0.90385 | 0.94000 | 0.92157 | 100 |
| 6 | 0.76230 | 0.93000 | 0.83784 | 100 |
| Micro average | 0.82429 | 0.82429 | 0.82429 | 700 |
| Macro average | 0.83858 | 0.82429 | 0.82234 | 700 |
| Weighed average | 0.83858 | 0.82429 | 0.82234 | 700 |


**Fig. 18.** Accuracy of proposed model

## 7. CONCLUSIONS,LIMITATIONS AND FUTURE SCOPE

The proposed model clearly classifies better than the traditional model. The main reason being the number of parameters in the traditional models are very big in proportion compared to the training data size (5600 images). Thus the model does not train well and acts as a random classifier. One more observation is that the precision of class one is less and the recall of class 2 is also less. This means that the class 1 images are misclassified as class2. Thus the CNN does not classify these two classes accurately. This problem can be overcome if we process class 1 separately using image processing techniques. The class 1 images are straight lines so using Hough transforms, we can setect easily whether a straight line is present or not. So we can train the CNN with the rest of the 6 classes.

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