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Mosquito Detection using Deep Learning based on Acoustics

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Abstract: ***Deep learning based techniques are becoming popular because of its stability. Success of voice analytics can be seen because in various applications like alexa, siri etc. Behind the scenes main concept is to generate and analyze features so that it can be applicable in real world. In this paper we are proposing a deep learning based pipeline for mosquito detection. Hardware integration with software techniques will create device that can meet need of end user. Further AI Nano Jetson and flying machine are used to complete the end goal.***

Keywords: deep learning, dense convolution networks, Feature Pre-processing, acoustic.

1. INTRODUCTION

Malaria, chikungunya, dengue, yellow fever, filariasis are some problems caused by mosquitoes. Their behavior of disease transmission is responsible for number of deaths. Lots of efforts have been taken to prevent their harmful impacts with the help of insecticide. Proper detection of harmful mosquitoes will be important step in their mitigation. Acoustic analysis is one of the important step in this direction but it contains various challenges like identification of weak signal that is merged with noise. In order to solve this problem various classification techniques can be used like neural network, support vector machine, random forest, decision tree etc. Since the data belongs to acoustic category, conventional machine learning techniques will not be suitable for the desired task. Deep learning techniques would prove itself better in this scenario.

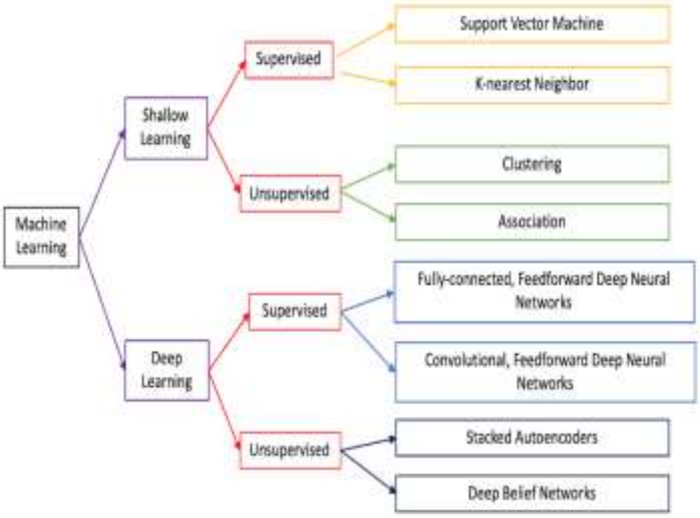


Figure1: Deep Learning Techniques

Further section provide details about literature of this field and experimental needs and process required to complete the desired task.

2. LITERATURE REVIEW

Past literature shows the use of machine learning and deep learning techniques for acoustic detection of species, sound can be used for variety of purposes like biodiversity analysis etc. Following table represents some important papers from past literature.

Table 1. Comparative analysis of recent work

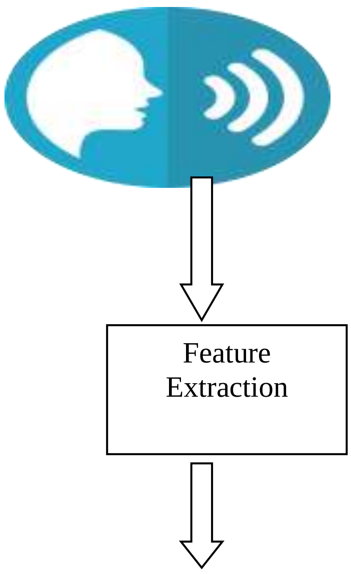
S.No	Year	Title	Technique and Results
	2018	Bat detective-Deep learning tools for bat acoustic signal detection [1]	Authors used Convolutional network (depending upon source pipeline) for identifying search-phase call by echo locating bats.
	2017	Automatic classification of furnariidae species from the paranaense littoral region using speech related features and machine learning [2]	Authors used multilayer perceptrons, support vector machines and ransom forest and found best classification rate approx 90%.
	2017	Automatic Insect detection using acoustic feature based on sound generated from insect activities [3]	Authors did test on 11 insects of six species using ensemble classifier and found 97.1 and 92.3% accuracy for species classification and insect classification respectively.
	2018	Application of acoustic emission and machine learning to detect codling moth infested Apples [4]	Authors used LDA (linear discriminant analysis) and ensemble adaptive boosting, finally obtained 91% to 100% , 83-100% accuracy for training and testing dataset respectively.
	2017	Detection of wood boring insects' larvae based on acoustic signal analysis and the artificial intelligence algorithm [5]	Detection of old house borer's detection is done by support vector machine and found to be effective in terms of classification accuracy.

	2017	Fusing shallow and deep learning for bio acoustic bird species classification [6]	Authors used deep Convolutional neural network with data augmentation on 5428 flight calls of 43 different species and obtained 96% accuracy.
	2016	Towards the automatic classification of Avian flight calls for Bio-acoustic monitoring [7]	Authors used unsupervised feature learning method
	2016	Deep learning for detection of bird vocalisations [8]	Authors used deep auto-encoders for identifying bird activity that will lead to biodiversity matters.
	2016	Using multi-label classification for acoustic pattern detection and assisting bird species surveys [9]	Authors used three multi-label classifiers for detecting five acoustic patterns and found proposed method suitable in typical weather conditions.
.	2015	Sparse coral classification using deep Convolutional neural network [10]	Authors used supervised deep Convolutional neural network.
.	2015	Effective insect recognition using stacked Autoencoder with maximum correntropy criterion [11]	Authors took deep Convolutional neural network with maximum correntropy criterion and found 92.1% accuracy on five species of insects, total 5325 passages.
.	2014	Automatic large scale classification of bird sounds is strongly improved by unsupervised feature learning [12]	Authors used random forest classifier on twelve different feature representation and performed empirical analysis.

3. EXPERIMENTAL DETAILS

Dataset is very important part to perform any analysis. We are using dataset from: https://github.com/HumBug-Mosquito/ZooniverseData.

This dataset has been collected from four sources and past analysis has also been performed on this dataset. Process architecture includes input data as voice samples then architecture mentioned [13] will be used to generate embedding for detection and separation. Finally the trained and locally tested model will be deployed on hardware device.



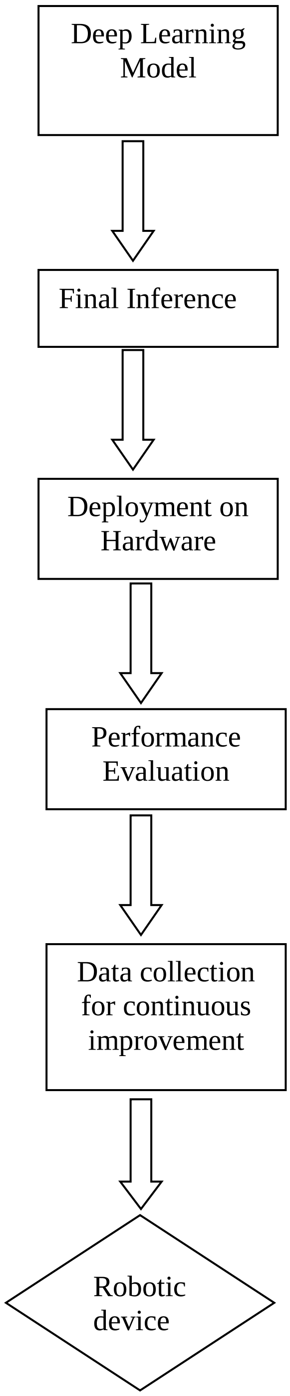


Figure2: Proposed framework

In order to sort out this issue already lots of deep learning techniques have been used. Impact of basic Convolutional neural network and its simpler variation is well explored. We explored the possibility to improve process pipelined using latest technique mentioned in [13]. Model architecture is shown in following figure.

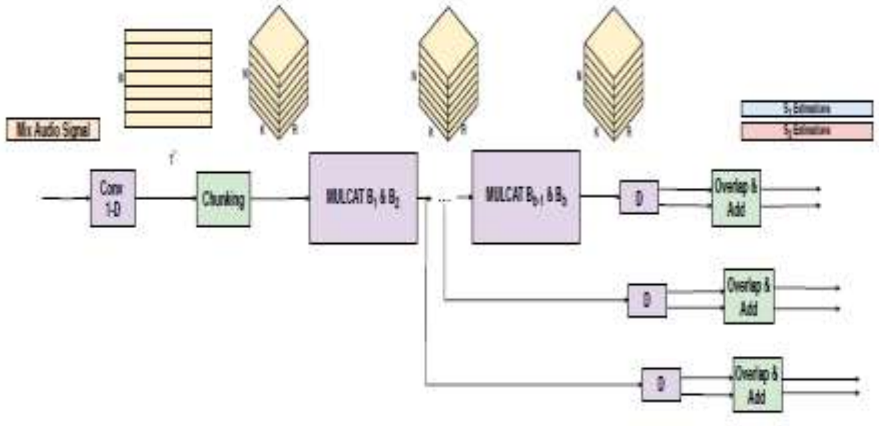


Figure3: Model Architecture [13]

In this architecture gated neural networks are used and this model outperforms and address cocktail party problem. We used this technique on our dataset and found satisfactory performance. Second part is to integrate this model to hardware component so to achieve this task we are using AI nano Jetson and flying machine.

Figure4: NVIDIA Nano Jetson

Figure5: Flying Machine

4. CONCLUSION

Prediction models based on deep learning are used for various applications of voice base applications. We have taken gated network for performing this task. Feature extraction and processing are quite efficient in this network and hence provide capability to sort out the core concern addressed in this paper. Hardware integration and deployment of deep learning model is another big challenge. In initial attempts we found big delay in the system. These delays may not be accepted for real world tasks. Delay reduction and optimization is not explained in this paper. We are also improving that part so that expected results can be attained when we go for mass production. Selection of other deep learning architectures and data set enhancement is left open for future work.

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