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Quintessential Aspects of Machine Learning Algorithms used for Animal Species Classification

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Abstract—

Species classification is an essential step of many biological researches. Manual processing of images for species identification and classification is highly time consuming. Manual processing is error prone also. Due to high noise level of input images preprocessing is also a challenging task. This paper mathematically analyses some of the algorithms which can be best utilized for species classification. This paper studies the working theo- ries of those algorithms and also discusses the applicability in species classification area. These machine learning algorithms are highly capable of making significant contribution to the animal species classification area.

Keywords- Deep Learning, Convolution Neural Network, SVM, KNN

I. INTRODUCTION

There are many machine learning algorithms which can be effectively utilized for animal species classification. Manual classification species using the images is highly time consuming. Especially when we are trying to classify marine species. Complex under water environment will make the classification highly difficult. Such images also contain a lot of noises which makes the manual classification nearly impossible.

Deep learning algorithms can contribute a great deal in this scenario. Deep learning algorithms have high feature learning capability which can be utilized for processing the images efficiciently even if it contain a lot of noises . Deep learning algorithms like CNN are proved to be highly effective in this problem domain. This CNN based networks can extract the features from the input image effectively and then based on these features they can classify the data into different classes. Pooling functions can be utilized along with the CNN layer to improve the efficiency of the system. Different types of pooling like max pooling; min pooling and average pooling can be used for this purpose. Selection of proper activation function is also a key point to consider. This paper reviews some of the deep learning based implementations which can be effectively utilized for animal species classification. Also the paper analyses the mathematical functions which are the key functionalities of these networks. This paper progresses in such a way that in upcoming sections it will go through some related work in the animal species classification area, some of the applications of the deep learning algorithms followed by analysis of various mathematical functions used in these implementations.

II. RELATED WORKS

In paper [1] authors describe a central coefficient based method for animal species identification. Authors perform a TESPAR analysis in order to generate the input data. In paper [2] authors use a multiple CNN network to perform the classification tasks. In this approach each CNN layers are separately trained and then the output of each of these units will be combined together. Support vector machine (SVM) algorithm is also used along with CNN to improve the overall efficiency. G. Chen et al. [3] discuss about an animal species classification algorithm using deep convolution neural net- works.

In paper [5] C. Lammie et al. talks about a weed species classifications using DNNs . The proposed architecture is highly efficient in weed classifications in robotic weed control. The proposed implementation is tested using a publically available dataset called Deep Weed. H. Wang et al.[6] use a deep learning based implementation for giant panda classification . They have used the face images of giant pandas to perform the classification. The dis- tinctiveness of panda face is identified using a deep learning based network for the purpose of classification. S. Schneider et al. [7,38-40] talk about a deep learning based method for object detection in an ecological dataset. The experiments are performed using two deep learning classifiers namely R-CNN and YOLO[30-36]. Authors proved that R- CNN outperform the other one for the selected dataset. This implementation proved the efficiency of using deep learning based implementation in automatically annotating the data set. It proved to be highly efficient comparedto its manual counterpart[26-29].

W. Zhang et al. [8] use a deep convolution network based implementation for shark behavior analysis. In this pa- per authors described a CNN based implementation to classify four different shark behaviors. Authors [6-10] have designed three CNN based networks to make the predictions[44,45,46]. In paper [11-18] F. Han et al. describe about a convolution neural network based implementation for fish shoal behavior analysis. In this implementation authors have created a convolution neural network based implementation to quickly identify the fish behavior[19-25]. This implementation proved to be effective in classifying different behavior state of the fish species under consideration[41,42,43].

III. MATHEMATICAL ANALYSIS OF ALGORITHMS USED FOR ANIMAL SPECIES CLASSIFICATION

In this section authors described about various machine learning algorithms which can be utilized for animal species classification. The mathematical functions used in each of these algorithms are studies and explained in great details. Algorithms like support vector machine, convolution neural networks, recurrent neural network, K nearest neighbor, artificial neural network etc are studies in detail

A. *Artificial Neural Networks*

Artificial neural networks are computational models which work on the basis of how human neuron works. This model imitates the working of biological neurons. This model consists of multiple layers connected with links. Each link has a specific weight. The output of one layer will be passed to the next layer. There are mainly two types of artificial neural networks. Feed forward and feedback networks. The diagram showing feed forward and feedback neural network is given below Figure 1 and figure 2

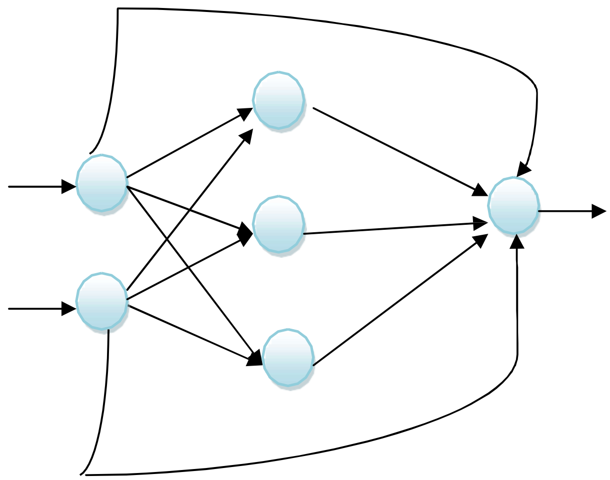


Fig .1 .Feed forward network

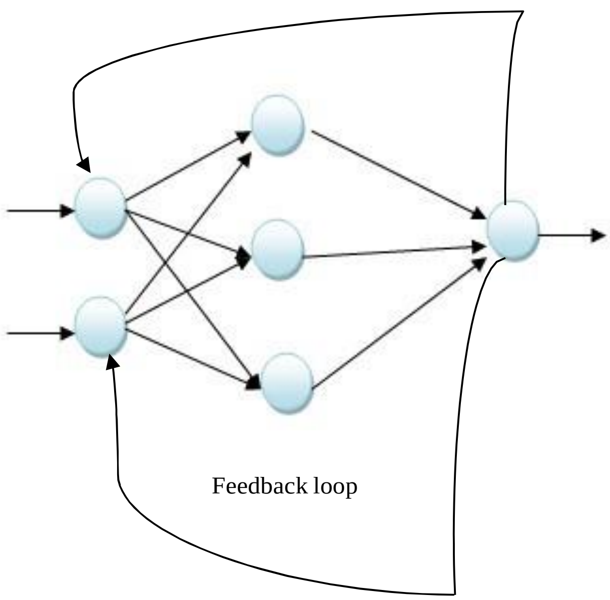


Fig .2 .Feedback network

In feed forward artificial neural network as shown in Fig.1 the information flows unidirectional. No feedback loop is involved in it. There is no cycle present in the network. On the other hand in feedback network there is possibility of bidirectional information flow. A feedback loop is present for the opposite directional information flow. In a simple multilayer artificial neural network the output activities of a neuron in a layer can be expressed as a simple function of activities of neutrons in other layer .

$$X_i = S\left(\sum_{j=1}^{N} W_{ij}Y_j + B_i \right)$$

Here Xi is the activity of i^{th} neuron and Y_1…. Yn are activities of neurons in other layers. Wij is the weightfunction and Bi is the bias function.

Sigmoid functions can be effectively used in the feed forward network. The sigmoid function is representedby the formula

$$S(x) = \frac{1}{1+e^{-x}}$$

The graph showing the sigmoid function is given in figure 3.

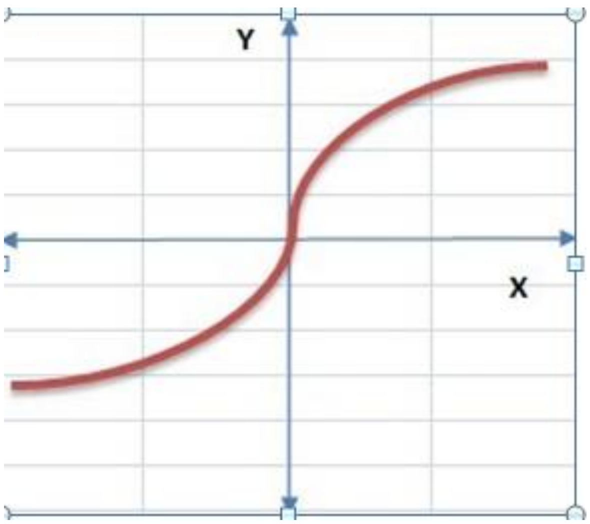


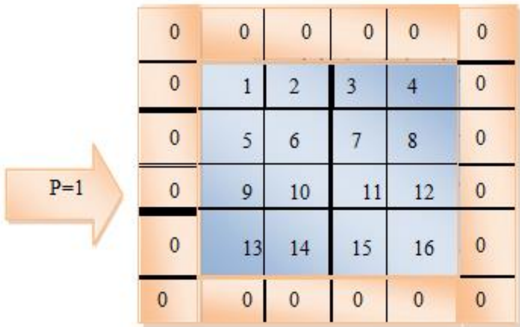
Figure 3 . Shape of sigmoid function

The backward propagation link in feedback network is used to adjust the weight at each layer so that the error canbe reduced.

B. Convolutional Neural Networks

CNN is highly efficient in applications like image processing, face identification, object classification, natural language processing etc. CNN consist of a series of convolution and pooling layers and at each layers the prominent features will be extracted and passed to the next layer. Different types of pooling like max pooling; min pooling and average pooling can be used for this purpose. The preprocessed image is given to the convolution network as an input. The CNN architecture will extract the features at each layer and finally able to classify the data based on prominent features. Padding and stride are two operations used in the CNN implementation.

Padding is mainly used to avoid the lose of edge data of the image. In order to avoid the loss of data present at the edge of the image we will pad the image with zeroes. The padding parameter (P) represents the padding used. Figure 4 shows the padding of an image matrix with P=1.



Stride is a parameter which determines the number of pixel on which the filter is applied. For example if the stride is one we will move the filter over one pixel at a time. As the size of stride increase the output size will decrease.

The convolution product between the filter K and image I is represented by the formula given below

An image can be mathematically represented as a function of number of pixels along the height (n_H), width(n_W) and the number of channels (n_C) . The mathematical representation is given below.

$$Dimension(image) = f(n_{H}, n_{W}, n_{C})$$

The convolution product between the filter K and image I is represented by the formula given below

$$\mathbf{Convolution(I,K)_{x,y}} = \sum_{i=1}^{n_H} \sum_{j=1}^{n_W} \sum_{k=1}^{n_C} K_{i,j,k}\, I_{x+i-1,y+j-1,k}$$

Pooling function is used in between the convolution layers in a CNN implementation. There are three types of pooling available namely max pooling and average pooling. The max pooling function will return the maximum value of the all selected values and average pooling will return the average of all selected values.

A python code showing the implementation of max pooling function is given below in figure.5

```
import numpy as np
from keras.models import Sequential
from keras.layers import MaxPooling2D


image = np.array([[42, 28, 78, 30],
                  [90, 40, 65, 10],
                  [87, 57, 20, 46],
                  [39, 10, 25, 76]])
image = image.reshape(1, 4, 4, 1)

model = Sequential(
    [MaxPooling2D(pool_size = 2, strides = 2)])

output = model.predict(image)


output = np.squeeze(output)
print(output)

[[90 78]
 [87 76]]
```

Fig 5: Implementation of max pooling

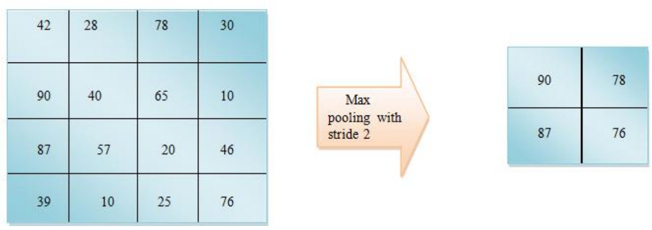


Fig 6 .Max Pooling

Here we are using a filter of size 2by 2 over the data with stride=2.

The calculations are performed as shown below.

Max (42, 28, 90, 40) = 90

Max (78, 30, 65, 10) = 78

Max (87, 57, 39, 10) = 87

Max (20, 46, 25, 76) = 76

The values 90, 78, 87 and 76 will be passed to the next layer of CNN network.

An illustration of average pooling is given below.

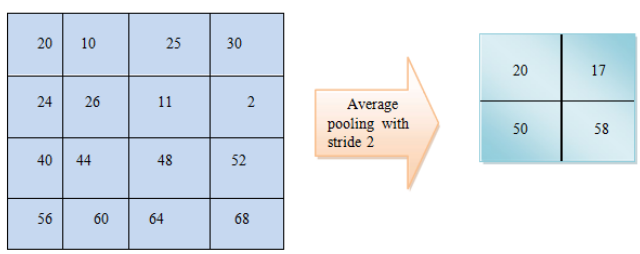


Fig. 7 Average pooling

The calculations performed are given below

Average (20, 10, 24, 26) = 20

Average (25, 30, 11, 2) = 17

Average (40, 44, 56, 60) = 50

Average (48, 52, 64, 68) = 58

The values 20,17,50,58 will be passed to next layers.

The values 20,17,50,58 will be passed to next layers.

C. Support Vector Machine

Support vector machine algorithm works by finding an optimal hyper plane which separate the data. Depending on the number of features under consideration the optimal plane can be a single dimensional line or a plane having more than one dimension. The points close to the hyper plane are called support vectors. If the separating plane is a line then it can be expressed as

$$W^T(x) + b = 0$$

Where b represent the bias.

For example if we have to classify the data into positive and negative group we will do the comparison as shownbelow

$W^T(f(x)) + b) > 0$ then the data point belong to positive class.

$W^T (f(x) + b) < 0$ then the data point belongs to negative class.

A diagrammatic representation of support vector machine algorithm is given below.

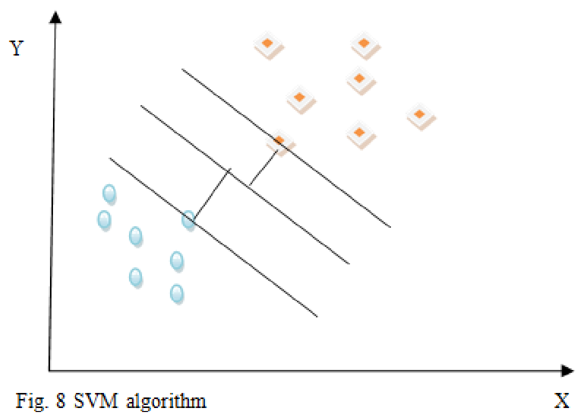


Fig. 8 SVM algorithm

IV. ANALYSIS OF APPLICATION OF MACHINE LEARNING ALGORITHM IN ANIMAL SPECIES CLASSIFICATION

In this section authors review about existing work on the animal species recognition using machine learning algorithms

A. Study of wild animal classification using machine learning

In one of the paper (Michael A. Tabak, Mohammad S. Norouzzadeh et al. (2019)) authors describe about an artificial neural network based model for identifying wild pigs from camera trap images. The authors describe that the model will have high level of accuracy in identifying the wild pig from the camera trap images. Authors claim to obtain the accuracy of 97.5%. Also because of the models ability to process the images from camera trap, this method can have very good application in the ecology and wild life research areas.

In another paper titled 'Animal species classification using machine learning techniques' (Fahad Alharbi *, Abrar Alharbi, and Eiji Kamioka 2019) authors discuss about multiple feature extraction to identify predator animals. This model uses the support vector machine and multilayer perceptron algorithms to extract the features of eye, ear of predator animals. In this papers authors discussed about animal identification technique by using various image processing techniques. Predator's pupil features and ear features are prominently used in this model to classify them. The important steps described in the paper are explained as follows (Michael A. Tabak, Mohammad S. Norouzzadeh et al. (2019)). First step is the collection of dataset containing the images of both predator and pet animals. From these region of interest is identified. Then the dataset is split into training and testing. The model is then trained using this training data set. This trained model is then tested against the test dataset. Two different classification algorithms namely support vector machine and MLP were used. These algorithms are taking the extracted features as input and they classify the data into two classes pet and predator. The precision and accuracy obtained by using the SVM method as described in the paper (Michael A. Tabak, Mohammad S. No- rouzzadeh et al. 2019) is given below

	Precision	Recall
Pet	0.769	0.8
Predator	0.792	0.76

Table.1 Precision and Recall for SVM algorithm

Similarly the precision and accuracy obtained by using the MLP algorithms are given below (Michael A. Tabak, Mohammad S. Norouzzadeh et al. 2019)

Similarly the precision and accuracy obtained by using the MLP algorithms are given below (Michael A. Ta bak, Mohammad S. Norouzzadeh et al. 2019)

	Precision	Recall
Pet	0.786	0.88
Predator	0.864	0.76

Table.2 Precision and Recall for MLP algorithm

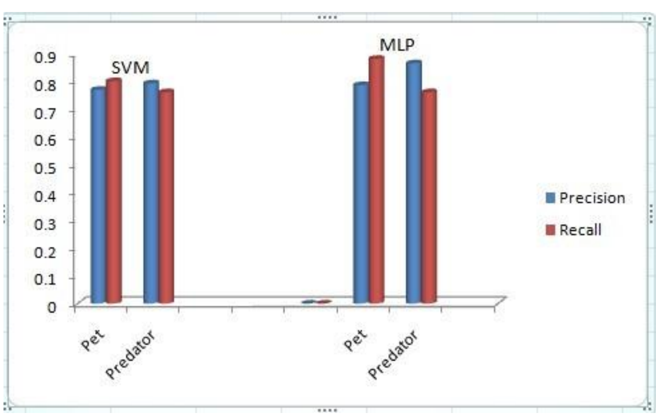


Fig 9: Representation of the data as a graph below (Michael A. Tabak, Mohammad S. Norouzzadeh et al.

2019)

Fig [9] will display the data as a graph .

Other measures to evaluate the model are true positive rate (TP), which is the ration of number of actual positive cases to the number of total positive cases. False positive (FP) rate is the ratio of number of actual positive case to the number of positive cases that should have been returned by the model (Michael A. Tabak, Mohammad

S. Norouzzadeh et al. 2019). TP and FP for SVM algorithm as given in the paper is shown below (Michael A. Tabak, Mohammad S. Norouzzadeh et al. 2019).

	TP	FP
Pet	0.8	0.24
Predator	0.76	0.2

Table.3 TP and FP for SVM algorithm

TP and FP for MLP algorithm as given in the paper is shown below (Michael A. Tabak, Mohammad S. No- rouzzadeh et al. 2019).

	TP	FP
Pet	0.88	0.24
Predator	0.76	0.12

Table.4 TP and FP for MLP algorithm

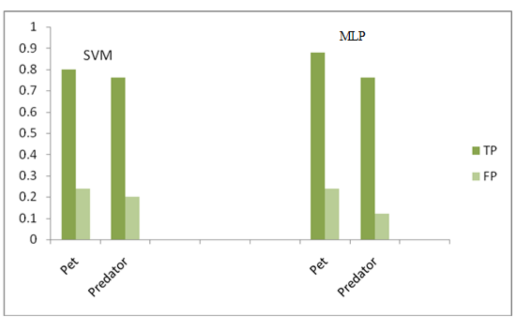


Fig 9: Representation of the TP and FP data as a graph below (Michael A. Tabak, Mohammad S. Norouzzadeh et al. 2019)

Figure 9 shows the graphical representation of TP and FP data

These accuracy measures show promising results for the application of machine learning algorithms for animal species classification.

B. Review of fly Species classification using machine learning algorithms

In the paper titled 'Research on Recognition of Fly Species Based on Improved RetinaNet and CBAM' (Y. Chen et al. ,2020) authors proposes a fly species recognition method using machine learning. Authors have used RetinaNet and Convolutional Block Attention module (CBAM) based model for this purpose. Authors claimed to have an average precision of 90.38% which is very promising. (Y. Chen et al.: Research on Recognition of Fly Species Based on Improved RetinaNet and CBAM ,2020). This model can effectively identify fly species con- taining pathogens. Improved RetinaNet model is used to identify fly species. It uses ResNeXt for feature extrac- tion. Convolution block attention module (CBAM) is used to remove the un important features from the model (Y. Chen et al.: Research on Recognition of Fly Species Based on Improved RetinaNet and CBAM ,2020). This CBAM uses the max pooling and average pooling to reduce the special dimensions. Probability bases stochastic pooling also utilized by the CBAM module. Fig.9 shows the spatial attention model used by the model. The accu- racy of the model is assessed in terms of precision and recall.

In similar studies (K. Li and J. C. Principe,2017) authors proposed an automatic insect detection model and evaluated the performance of the model with similar models. Other neural network based models like VGG, ResNet (K. Simonyan and A. Zisserman 2014, S. Xie et al. 2017) are also proved to be very effective in the fly species identification and classification. VGG is a model in which network performance is increased by adding convolution and max pooling layer in between the network (K. Simonyan and A. Zisserman 2014) . For Resnet model the complexity of the network is minimal compared to VGG and it is much deeper model. Attention models are being used in various implementations (F. Wang et al. 2017). Attention model tries to extract features at important location result in better performance and less energy consumption (Y. Chen et al.,2020)

Yao et al (Yao et al ,2012) used SVM classifier to classify different classes of pests . Combination of artifi- cial neural networks and support vector machine algorithms are being used by Wang et al. in the paper. (Wang et al, 2012) .Due to the fact of manual feature extraction the accuracy obtained by this model is less. Hu et al pro- posed a deep learning based method for animal species detection (Hu et al.2018). This model uses a squeeze and extract module to extract global features. The model will focus more on the channel feature with most informa- tion using the attention mechanism (Hu et al. 2018)

These mechanisms discussed are effective in identifying the fly species.

C. Review of Frog classification using machine learning algorithms

This section reviews some of the frog classification models implemented with the help of machine learning algorithms. In the paper titled 'Frog classification using machine learning techniques' authors describe about a frog species classification using support vector machine and k nearest neighbor algorithm(Chenn-Jung Huang et al.2009)

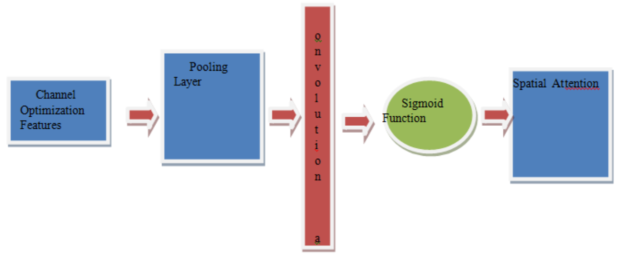
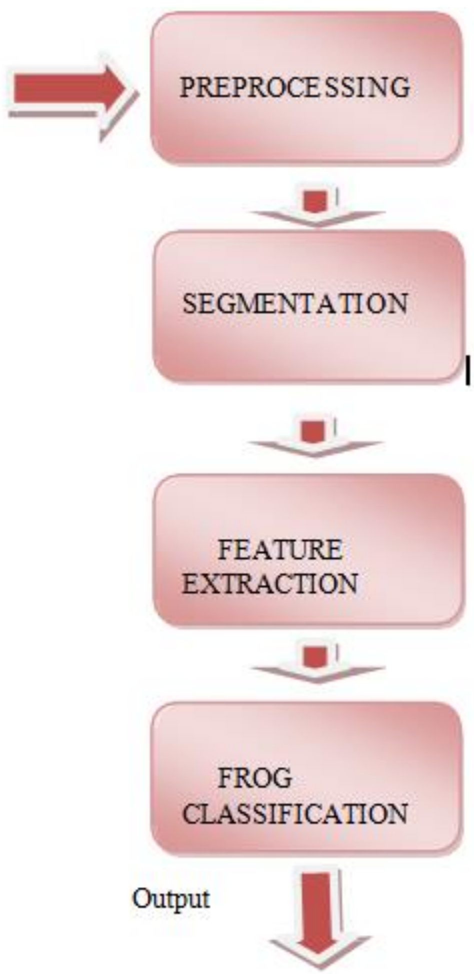


Fig 9.Spatial attention mod

The proposed model consists of four main components or modules. They are pre processing module, segmentation module, feature extraction module and classification module (Chenn-Jung Huang et al.2009). In the preprocessing module the recorded signal is sampled at certain frequency. In the segmentation unit syllables are segmented. Due to the reverberation syllable segmentation is a challenging task. After the segmentation features are extracted in the feature extraction module. Finally the classification module will classify the data into various frog species (Chenn-Jung Huang et al.2009). Figure 10 shows the architecture of the frog classification mode



Fish species classification using deep learning

Aquatic fish species classification can be effectively performed using deep learning. Convolution neural networks can be effectively used for fish species classification. Images of under water fish can be given as an input to the implementation. The CNN architecture will perform the feature extraction and based on these features we can identify and classify fish species from the input image. The architecture of such implementation is given below.

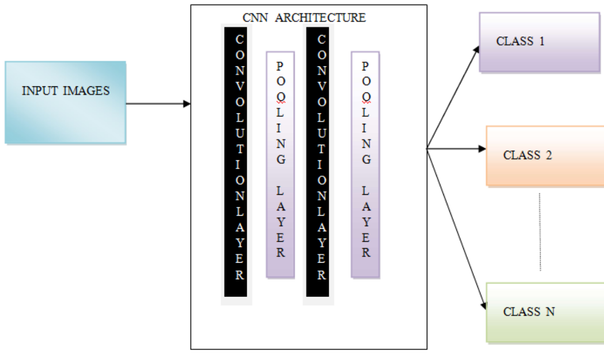


Figure 9. CNN based fish classification architecture

Some sample images from the *LifeCLEF 2015[13] dataset is given below.*

Fig.10. A sample training data set images from *LifeCLEF 2015[13]* dataset

Another set of sample training data set images of 'Amphiprion clarki 'species is given below in fiure.11

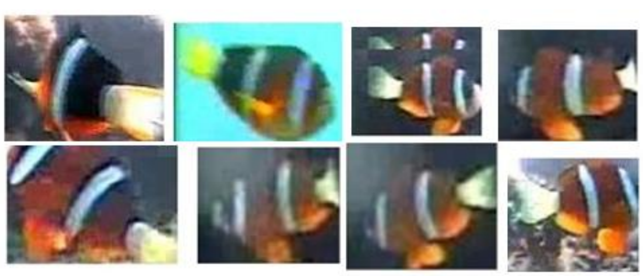


Fig.11. A sample training data set images from *LifeCLEF 2015[13]* dataset

In paper [12] authors discuss about a similar implementation. They have implemented a CNN based fish spe- cies classification model using convolution neural network. Authors have used fish4knowledge data set for their experiment and the CNN based system has shown promising efficiency values. D. Rathi et al. have implemented a DeepCN architecture using CNN network. In addition to that they have implemented hybrid models by combin- ing CNN and SVM, CNN and KNN. The hybrid model using CNN and KNN showed better accuracy values thanthe other two models [12].

In this paper authors studied about some of the animal species classifications models available. Various algo- rithms which can be utilized effectively also discussed. Authors also gave an overview of the working of some of the algorithms like support vector machine, K nearest neighbor and artificial neural networks. Further authors studied about various types of animal species detection models like wild animal detection, frog species classifica- tion, fly species classification and fish species classification. Various algorithms used for each application that are being studied are listed below

Type	**Algorithms Used**
Wild animal species classification	SVM ,MLP
Fly species classification	Neural networks ,SVM
Frog species classifica- tion	SVM ,KNN
Fish species classifica-tion	SVM , Deep learning

Some of the criterions and decision parameters for selection of the algorithms are the complexity of the input data set, requirements of the model and expected output from the model. By wisely selecting and implementing the correct model, promising results will be obtained.

As a future work authors are planning to implement a deep learning based model which can be efficiently classify marine species. This survey is the first step towards the implementation of the proposed model.

V. Major Contributions of the paper

This section lists some of the contributions of the paper. The paper performs an analysis of how some of the famous machine learning and deep learning algorithms works. It reviews the mathematical functions which are used in these implementations. Moreover paper emphasis on the benefit of using machine learning algorithms for animal species classification. Compare to its manual counterpart, usage of machine learning algorithm is highly beneficial. Some implementations from existing literature are also discussed. These implementations prove the efficiency of machine learning algorithms in animal species classification.

VI. Conclusion

The paper emphasis on the benefit of using deep learning based algorithms for animal species classification. Compared to the manual classification, deep learning based methods are highly efficient .Manual classification is time consuming and error prone .Also if we are using manual process the preprocessing will be a challenging issue. The amount of preprocessing required in images will be less if we are using CNN like algorithms due to its high feature learning capability. It is a great advantage as the images from unconstrained environment like ocean underwater will contain a lot of noises. CNN based implementation can effectively remove the noise and capable of identifying the species under consideration successfully. The mathematical analysis of algorithms through light into how these algorithms works from a functionality point of view. Authors are working on building an efficient algorithm for classifying the marine fish species. This analysis is an initial step towards it.

Declarations

Ethics approval and consent to participate: Not applicable
Consent for publication: Not applicable
Availability of data and materials : Data is available
Competing interests: The authors declare that they have no competing interests
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