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CNN Based Acute Rheumatic Fever Vitality Data Analysis Decision Model

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ABSTRACT

The autoimmune disease which infected by group Astreptococcus in human beingsis Acute Rheumatic Fever (ARF). The major symptoms identified especially in connective tissues, heart, joints, skin and brain. The analysis of ARF disease is affected by warms or not is the major investigation research. The research show 1/6th of human population is affected by worms and is one of the neglected tropical diseases also. It is found where access to personal hygiene and proper sanitation practices are not available and in places where human faeces are used as fertilizer. The paper proposes predictive analysis of ARF by the effect of worms that are alive or dead using pre-trained Convolutional Neural Network. The analysis is based on real images of microscope slides where core measures characteristics are alive worms are round and dead worms are straight.WormImage database with 93 microscope slide worm images are considered for validation and simulation is tested with Python platform. The evaluation of model shows that accuracy and f1 score for alive worm 100% and 0.9071 and for dead worm is 86% and 0.924 respectively.

Keywords: Acute Rheumatic Fever, CNN, Positive rate, max-pooling, F1 score

INTRODUCTION

The worms are free-living organisms, but they are probably best known for their role as significant plant and animal parasites. Most Nematodes are parasitic with over 16,000 parasitic species are researched so far. Heartworms which cause serious disease in dogs while living in the heart and blood vessels are types of roundworm. Roundworms can also cause disease in humans. Elephantiasis disease characterized by the extreme swelling of limbs is caused by infection of roundworm. Most parasitic roundworm eggs or larvae are found in soil and enter the human body when person picks them up on hands and then transfers to the mouth. The eggs or larvae of roundworms can enter human body directly through skin which infect humans via faecal-oral route. Eggs released by adult females are shed in faeces. Unfertilized eggs are often observed in faecal samples but never become infective. Fertilized eggs embryonate and become infective after 18 days to several weeks in soil depending on environmental conditions.Fertilization can occur and female produces as many as 200,000 eggs per day for 12–18 months. Thefertilized eggs become infectious after two weeks in soil and they can persist in soil for 10 years or more.The diagnosis of Ascariasis is usually done with stool microscopy, eosinophilia, imaging, ultrasound and serology examination. Treatment is recommended for Ascariasis only if worms are alive in intestines and are large in number. To make such analysis, the paper proposed Convolution Neural Network based prediction model to predict worm is alive or dead rather than predicting based on structure, phase and sexuality of the worms in human intestines.

The input system is worm image and CNN to predict whether worms are alive or dead. In neural networks Conv-Nets isfor images recognition, images classifications, Objects detections, recognition faces etc. Technically, deep learning CNN models to train and test, each input image will pass it through series of convolution layers with filters (Kernals), Pooling, fully connected layers (FC) and apply Soft max function to classify an object with probabilistic values between 0 and 1. Pooling layers section would reduce the number of parameters when images are too large. Spatial pooling also called subsampling or down sampling which reduces the dimensionality of each map but retains important information. Max pooling takes the largest element from rectified feature map. Taking largest element could also take average pooling. Sum of all elements in feature map is called as sum pooling.

The classification of worms as alive or deadis performed using pre- trained convolutional neural network with images of microscope slides. Some of the microscopic slides contain both straight and round worms. These slides are labeled with majority type. The file is viewed as WormData.csv to see label assigned to each slide. The project files include images, labels, and solution script. Worm Images contains 93 microscopic images. Supervised learning is adopted as correct output is known and prediction by employing pre-trained convolutional neural network for binary classes (alive and dead) to achieve acceptable results in terms of loss and accuracy. Deep learninguses multi-layered structure of algorithms called neural networks. The traditional pooling layers are altered according to criteria and methods. Without transfer learning approach, prediction has been preferred to show the acceptable accuracy and concerned approach avoided use of unsupervised learning.

The organization of the paper is as follows. The literature survey is explained in section (2). Section (3) explains the proposed predictive decision model for worm vitality analysis.The design nconstraints of pooling layer and matrix methodology for CNNmodel which is used for statistical features and CNN features classification is depicted in section (4). The data flow analytical diagram for predictive wormsmodel is described in Section (5). Experimentation and result analysis isdepicts in section (6) and finally section (7) depicts concluding remarks.

LITERATURE SURVEY

Yang et al [1] has proposed computerized digital image processing algorithm for automatic routine faecal examination for parasitic disease. First, basic image processing tasks have been applied to the image, and segmentation of cells from background has been achieved using binary threshold. Morphological features are extracted from region of interest and fed to the artificial neural network to classify.Microscopic analysis and automatic diagnostic can be extremely repetitive laborious and requires expertise to spend a tremendous amount of time. Machine learning and computer vision made this task possible by the use of current techniques.

The author [2] shows various flexible machine vision techniques for automatic analysis and diagnostic of microscopic images. In [3], author proposed robust technique to classify 16 types of various parasite eggs from microscope images. The framework includes three stages: first stage includes selecting unique features for each class and second stage includes feature extraction mechanism-based on invariant moments for classification, an Adaptive Network-based Fuzzy Inference System (ANFIS) to label each image with the type of parasite.

Usage of microscopic images is extensive in the healthcare field for diagnostic purposes due to its easy availability and its cost-effective characteristic. It is widely used in financially weak areas too. In [4], Quinn et al have proposed various methods to address automatic diagnostic of microscopic medical images. The author has represented improvement in performance of automatic diagnostic of medical images using deep learning and CNN architectures.Author in [5] has proposed an approach to detect eggs of three most common soil-transmitted helminth using computer vision and artificial neural network. The author proposed an android application for object detection using ANN called Kankanet app that can intake low-resolution microscopy images, process them, and indicates to the users that eggs of the worm are present there or not.

In [6], author proposed a cloud-based deep learning algorithm that can locate, classify and identify parasite eggs in the examination. The system proposed is called VETSCAN IMAGES. The main aim of software is an automatic facial examination and compares it with conventional facial examination.In [7], author has presented the development of various machine learning models for object identification of parasite eggs for microscope medical images. Modals aim to locate and classify parasite eggs from microscopy images.

The experiment in this work shows that R-FCN RasNet101 was the best model to identify parasite egg objects due to its high speed and performance capability compared to other models. Naruto et al [8] proposed another method to classify parasite eggs for the microscopy-based method. The optimal architecture of deep learning has been used in this work. The convolutional neural network has been used in this work. Ten layers of convolution have been deployed and input image is provided to a three-channel true-color image. The detail comparison of techniques to count eggs in facial examination has been presented in [9].

PROPOSED PREDICTIVE DECISION MODEL FOR WORM VITALITY ANALYSIS

To classify thewormsare alive or deadis performed using pre- trained convolutional neural network with images of microscope slides. The microscopic slides includeboth straight and worms and slides are labeled with majority type. Supervised learning is adopted as correct output is known and prediction by employing pre-trained convolutional neural network for the binary classes (alive and dead) to achieve acceptable results in terms of loss and accuracy. Without transfer learning approach prediction has been preferred to show the acceptable accuracy and concerned approach avoided the use of unsupervised learning. Fig.1 shows the design framework for worm vitality model.

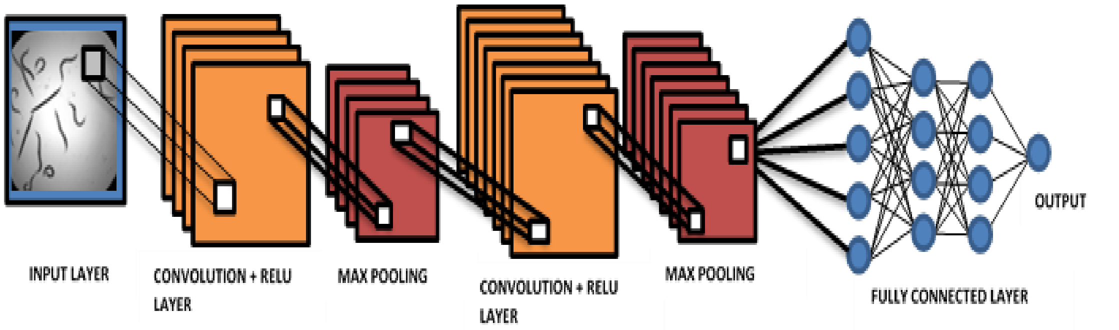


Fig.1. Design framework for worm vitality model

The convolution is performed on input data with kernel to produce feature map. It is a feed- forward neural network generally used to analyze visual images by processing data with grid-like topology. The input features are taken in batches like filters allows network to remember an image in parts and image is fed to input layer in the form of arrays. Every image is represented in the form of arrays with pixel values. Each image is namely represented as 3D matrix with dimension for width, height and depth. Depth is dimension or in other words the number of channels used in an image (RGB).

The hidden layers are convolution layer, ReLUlayer, Pooling layer, Flatten layer, fully connected layer or denselayer. Convolutional layers in neural network systematically apply learned filters to input images to create feature maps. It is very effective and allows layers close to the input to learn low-level features and layers deeper in model to learn high-order or more abstract features, like shapes or specific objects. It uses information from adjacent pixels to down-sample the image into features by convolution and then use prediction layers to predict target values. Each filter extracts different features from the image. An element-wise multiplication between image pixel values that match the size of kernel. The summation of value provides single value for feature cell.

The limitation of feature map output of convolution allayers is that they record the precise position of features in input. The small movements in position of feature in input image will result in different feature map. This can happen with re-cropping, rotation, shifting and other minor changes to input image. Aneural network learns those kernel values through back propagation to extract different features of the image. An activation function is used to make our output non-linear.

The pooling layer is responsible for reducing spatial size of convolved feature. This is to decrease computational power required to process the data through dimensionality reduction. It is useful for extracting dominant features which are rotational and positional invariant, thus it maintains process of training model. The addition of pooling layer after convolutional layer is common pattern used for ordering layers with in convolution alneural network that may be repeated one or more times in given model. The pooling layer operates upon each feature map separately to create new set of same number of pooled feature maps. The size of pooling operation or filter is smaller than size of feature map. There are two types of Pooling: Max Pooling and Average Pooling. Max Pooling returns maximum value from the portion of image covered by Kernel. Average Pooling returns average of all the values from portion of image covered by Kernel. Max Pooling also performs as Noise Suppressant. It discards the noisy activations altogether and also performs de-noising along with dimension alit reduction.

Average pooling simply performs dimension ality reduction as noises up pressing mechanism. Max pooling performs lot better than Average Pooling. After max-pooling, model will now understand the features and further, final output is flattened and is fed to neural network for further classification. The input image is converted into suitable form for Multi-Level Perceptron, and image is flattened in to column vector. The flattened output is fed to feed-forward neural network and back propagation applied to each iteration of training. In fully connected layer, input layer nodes are connected to every node in second layer. Adding fully connected layer helps learn non-linear combinations of high-level features outputted by convolutional layers. Activation function and dropout layer are used between two consecutive fully connected layers to introduce non-linearity and reduce over-fittingrespectively.Dropout is regularization technique used to reduce over-fitting on neural networks.

DESIGN CONSTRAINTS OF POOLING LAYER AND MATRIX METHODOLOGY FOR CNN

The design is explained as conv2d_1 (Conv2D) (None, 694, 518, 64), Parameter = 1792 Formula: Conv2D = ((shape of width of the filter * shape of height of the filter * number of filters in the previous layer+1)*number offilters) Conv2d= ((3*3*3+1)*64 = 1792 #number of filters in the previous layer = the no of channels considered in input shape as first layer in the model.

For unbiased comparison, the split of dataset into 25% as test set, 75% for training (30% of them are used for cross validation) as assumed. Image Preprocessing layers are for standardizing the inputs of an image model.

- Resizing layer: Resizes a batch of images to targetsize.
- Rescaling layer: Rescales and offsets the values of batch of image (e.g. go from inputs in the [0, 255] range to inputs in the [0, 1]range.
- Center Crop layer: Returns center crop of batch ofimages.

Images are also represented by bit patterns. In its simplest form, an image is composed of matrix of pixels (picture elements) where each pixel is small dot. The size of pixel depends on resolution. For example, an image can be divided into 1000 pixels or 10,000 pixels. In second case, there is better representation of image (better resolution), but more memory is needed to store the image. After an image is divided into pixels each pixel is assigned bit pattern. The size and pattern value depend on image. For an image made of only black- and-white dots, I-bit pattern is enough to represent pixel. If an image is not made of pure white and pure black pixels, increase the size of bit pattern to include gray scale. For example, to show four levels of gray scale, you can use 2-bit patterns. A black pixel can be represented by 00, dark gray pixel by 01, light gray pixel by 10 and white pixel by 11. There are several methods to represent color images. One method is called RGB, so called because each color is made of combination of three primary colors: red, green, and blue. The intensity of each color is measured and bit pattern is assigned to it.

For evaluating the results of work and comparing it to the selected model, same four metrics of performance measure is used. The four measures that are used in this comparison are commonly applied to classification problems and they are Accuracy (A), Precision (P), Recall (R), and F1-Score. They are defined in terms of true/false positives/negatives (Tp, Tn, Fp, Fn), where positive classes are those corresponding to alive images. We also introduced some other metrics such as Confusion Matrix which is a plot of True Positive Rate (TPR) versus False Positive Rate (FPR) at various threshold values to study how the discrimination threshold of our binary classifiers is varied and demonstrate the trade-off between false positives and false negatives.

Accuracy is the fraction of predictions the model got right, it could be a reasonable initial measure since the classes in our dataset are all of similar sizes and is computed as follows: -

A= Number of Correct predictions/ Total Number of Predictions

$$A = Tp + Tn / Tp + Tn + Fp + Fn \quad \ldots\ldots\ldots\ldots..(1)$$

Where Tp = True Positives, Tn = True Negatives, Fp = False Positives, and Fn = False Negatives
Precision reflects the fraction of reported alive images that are so (proportion of positive identifications was actually correct). It is calculated from the following formula:

$$P = Tp / Tp + Fp \quad \ldots\ldots\ldots\ldots\ldots\ldots..(2)$$

Recall as the fraction of alive images that are found by the classifier (proportion of actual positives was identified correctly).

$$R = Tp / Tp + Fn \quad \ldots\ldots\ldots\ldots\ldots\ldots.(3)$$

F1-Score is a measure of a test’s accuracy and is expressed in terms of Precision and Recall (Harmonic Mean between precision and recall), it could be considered as a measure that punishes false negatives and false positives equally but weighted by their inverse fractional contribution to the full set to account for large class number hierarchies.

$$F1 = Precision * Recall / Precision + Recall \quad \ldots\ldots\ldots\ldots(4)$$

$$FBR = Fp / Fp + Tn \quad \ldots\ldots\ldots\ldots\ldots\ldots.(5)$$

Confusion matrix contains the counts of occurrences of all the possible model prediction outcomes, for every classification there are four possible outcomes: If the model correctly predicts "Alive " image it is called True Positive (Tp) and if incorrectly classed as "Dead" image then it is a false negative (Fn). On the other hand, if the model correctly predicts the object to be "Dead" it is a true negative (Tn). But if classed as "Re" when it is not, then it is a false positive (Fp). Briefly, it contains the totalnumbers true/false positives/negatives. Fig. 2 shows the confusion matrix chart.

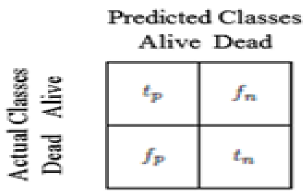


Figure 2: Confusion Matrix chart

DATA FLOW ANALYTICAL DIAGRAM FOR PREDICTIVE WORMS MODEL

The data flow diagram fig.3 depends on dataset for the classification and prediction of 93 microscopic slides. The collection of data is the first step in creating flow for calculations. Splitting of data assures the network is trained and tested for better output.Training Data is kind of labeled data set or annotated images used to train the artificial intelligence models or deep learning algorithms to make it learn from such data sets and increase the accuracy while predating the results.Testing data is quite different from training data as it is kind of sample of data used for an unbiased evaluation of final model fit on the training dataset to check model functioning.The correct output provided in the dataset for testing the accuracy of trained network.

Learning in convolutional neural network is the method of modifying the weights of connections between the neurons of specified network. Learning in CNN can be classified into three categories namely supervised learning, unsupervised learning, and reinforcement learning.During the training of CNN under supervised learning, the input vector is presented to the network, which will give an output vector. This output vector is compared with the desired output vector.Error signal is generated, if there is a difference between the actual output and the desired output vector. On the basis of this error signal, the weights are adjusted until the actual output is matched with the desired output.During the training of CNN under unsupervised learning, the input vectorsof similar type are combined to form clusters. When a new input pattern is applied, then the neural network gives an output response indicating the class to which the input pattern belongs. There is no feedback from the environment as to what should be the desired output and if it is correct or incorrect. Hence, in this type of learning, the network itself must discover the patterns and features from the input data, and the relation for the input data over the output.

Classification is the process of learning to distinguish data of samples into different classes by finding common features between the samples of same classes. For example, to perform training of CNN, we have some training samples with unique features, and to perform its testing we have some testing samples with other unique features. Classification is an example of supervised learning.Regression is set of methods for modeling the relationship between one or more independent variables and adependent variable. The purpose of regression is most often to characterize the relationship between the inputs and outputs.The predictions made in the hidden layer are collected to produce the final layer – which is the model's prediction.

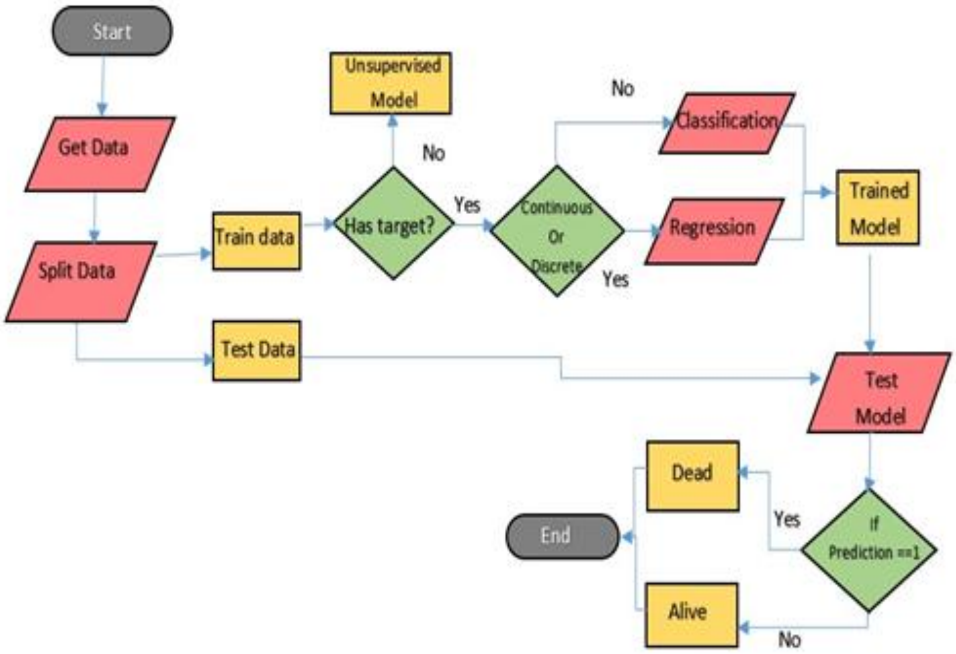


Fig.3. Data flow diagram to show the training and testing data

EXPERIMENTAL SET UP AND RESULT ANALYSIS

The main objective is to predict whether the roundworm is alive or dead in the microscopic image using convolution neural network (CNN). The diagnosis is based on X-ray imaging which is similar to microscopic slides. The acceptable result is obtained without overfitting.

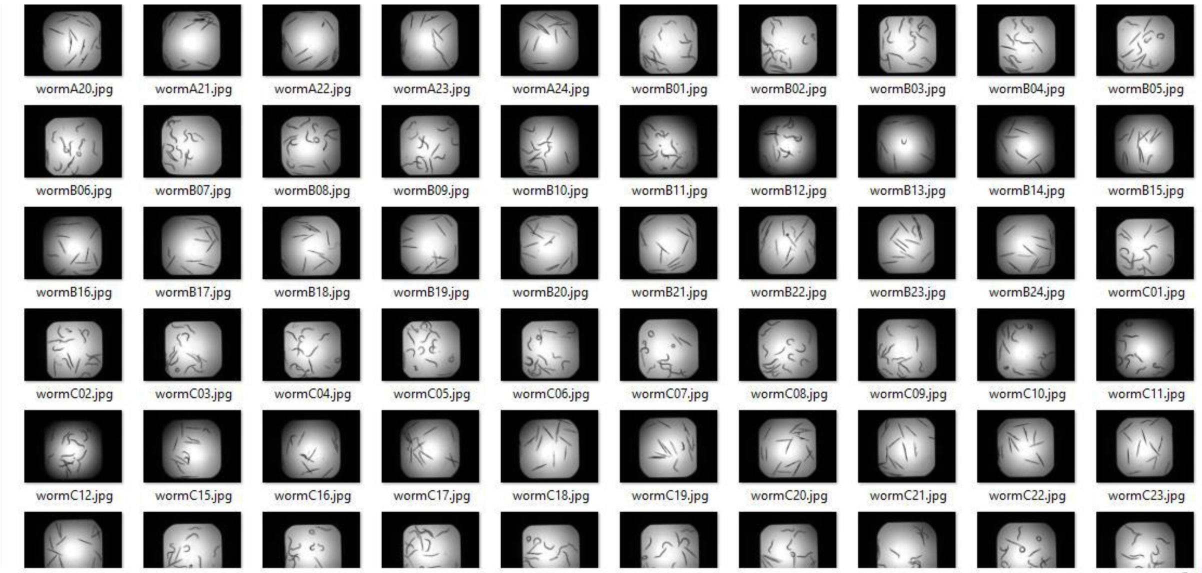


Fig.4 Referred worm data set for ARF vitality

The dataset shown in the fig.4 for research work consists of 93 images test data and train data. It has the necessary data for classification and prediction of the rheumatic fever attributes. The collection of raw data is the first step in creating flow for calculations. Splitting of data assures the network is trained and tested for better output. Training data is labelled data set used to train deep learning algorithms to increase the accuracy while predating the results. Testing data is quite different from training data sample used for an unbiased evaluation of final model fit on training dataset to check model functioning. The target is correct output in the dataset for testing accuracy of the trained network. Learning is the method of modifying weights of connections between neurons of a specified network. It is classified into supervised learning, unsupervised learning and reinforcement learning. Fig.5 Worm data set and visualization of data set.

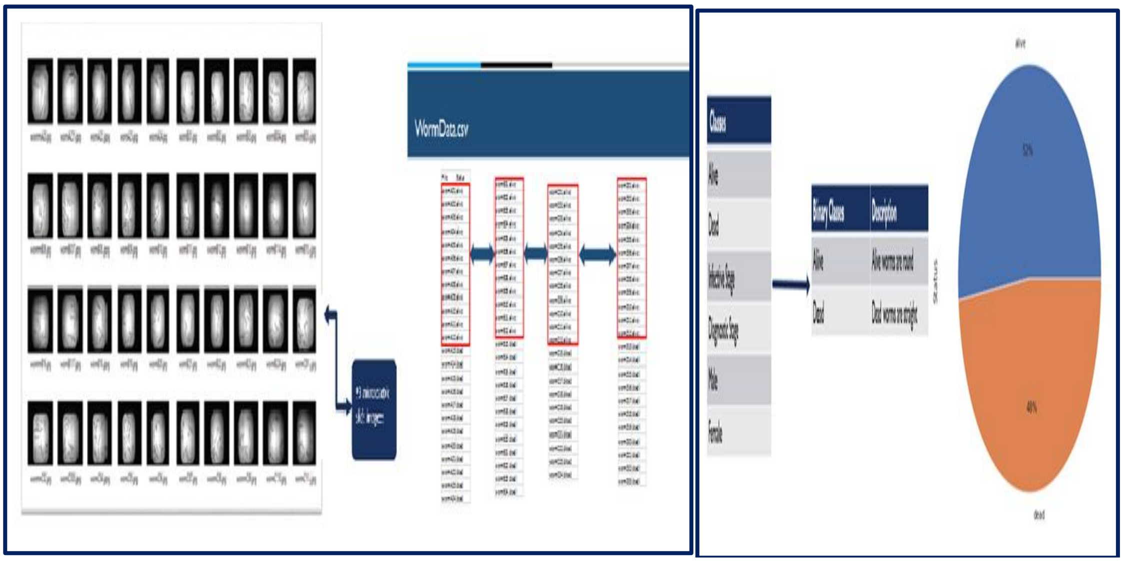


Fig.5 Worm data set and visualization of data set

During training of model under unsupervised learning input vectorsof similar type are combined to form clusters. When new input pattern is applied to neural network model which gives an output response indicating the class to which input pattern belongs. The type of learning where the network itself must discover the patterns and features from input data and relation for input data over the output. The classification is a process of learning to distinguish the data of samples into different classes by finding common features between samples of the same classes. Regression is set of methods for modelling the relationship between one or more independent variables anddependent variable. The purpose of regression is most often to characterize the relationship between inputs and outputs. The predictions made in the hidden layer are collected to produce final layer which is the model's prediction.Fig.6 processing of images using CNN.

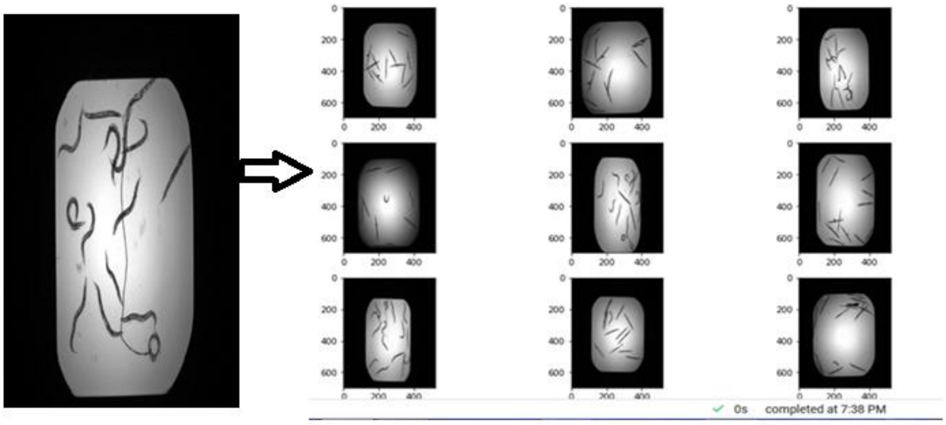


Fig.6 Processing of images using CNN

The output graph fig.7 represents outcomes of the train dataset. Diagonal represents true values of dataset and remaining are false values of dataset.

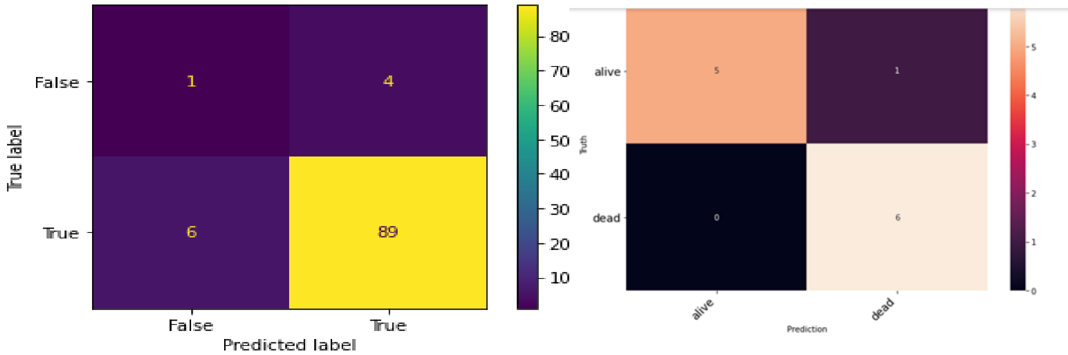


Fig.7 ARF predicted mapping result for training data sample

Similarly output graph fig.8 represents the outcomes of the test Dataset. Diagonal represents true values of dataset and remaining are false values of dataset.

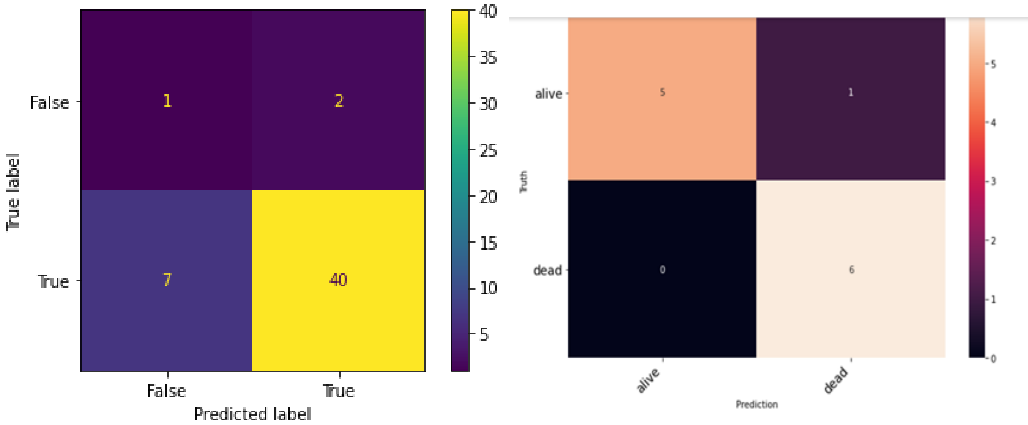


Fig.8 ARF predicted mapping result for test data sample

Table.1 shows accuracy comparison chart for two set of training and test data sample. The accuracy results in trail 1 comprise for 91.67± 0.05 for training time of 7.69m with 0.05 model dropout error, 92.45± 0.89 for training time of 10.67m with 0.89 model dropout error, 93.45± 0.50 for training time of 18.96m with 0.50 model dropout error, 94.78± 0.02 for training time of 21.56m with 0.02 model dropout error.

It concludes that maximum accuracy 94.78% is obtained at less model dropout error of 0.02. Similarly for trail 2, accuracy 91.23± 1.05 for training time of 19.78m with 1.05 model dropout error, 92.34± 0.08 for training time of 30.10m with 0.08 model dropout error, 93.46± 0.01 for training time of 38.38m with 0.01 model dropout error and 94.67± 0.03 for training time of 19.78m with 0.03 model dropout error respectively.

Table1. Accuracy Result of Train and Test dataset

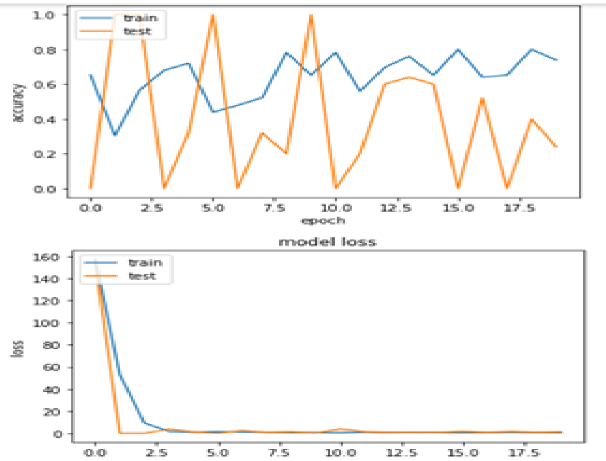
No of depths	Training Time1 (m)	Test Case I Accuracy	Training Time 2 (m)	Test Case II Accuracy
1	7.69	91.67±0.05	19.78	94.67±0.03
2	10.25	83.45 ±0.03	42.46	91.23±1.05
3	8.35	87±1.05	27.87	92.67±1.25
4	11.34	90.45 ±0.01	19.09	93.21±0.05
5	16.54	83.45 ±1.79	27.20	90.23±0.08
6	11.23	83.45 ±0.03	38.38	93.46±0.01
7	10.67	92.45 ±0.89	39.70	94.07±1.25
8.	21.56	94.78 ±0.02	26.92	91.67±0.05
9.	23.55	86.45 ±1.34	30.10	92.34±0.08
10	18.96	93.45 ±0.50	52.13	90.12±0.25

The training set is used to tune the model parameters where the model learns from training data. Table.2 shows Alive or Dead approximation using Recall & F1 Score. But in order to produce an independent measure of the model's performance test set is used. The final test is introduced and evaluation results including the characteristics of the classifier based on its performance on final to compare to prior work.

Table.2 Alive or Dead approximation using Recall & F1 Score

Attributes	Precision	Recall	F1- Score	Support
Alive	1.00	0.83	0.91	6
Dead	0.86	1.00	0.92	6
Accuracy	-----	------	0.92	12
Macro Avg	0.93	0.92	0.92	12
Weighted Avg	0.93	0.92	0.92	12

A suitable and acceptable accuracy on the test data is obtained substantially. The model with dropout layers performs the best on test data. As shown in figures 9 & 10 we tried to reduce over fitting.



By start training (pre-training and fine-tuning) the system using training data samples and stop training when the likelihood of validation data sets decreases for certain number of iterations. After training the system, we classify testing data samples using DBN. The highest percent count we achieve for testing individual channels is 94.33 and combining individual channel results with majority vote gives testing trial accuracy of 93.33.The average classification accuracy we achieved across all subjects is 94.38 for testing individual channels and 94.6 for testing trials.

CONCLUSION

In this paper, modified CNN network is developed in deep neural architecture which is implemented in 93 image datasets and its accuracy is tested against the normal Deep belief network. In the experimental results, our proposed system reached highest classification accuracy comparing with the existing DBN algorithm. For the first two dataset the depth, 92.45% gives best accuracy, while for the third dataset depth, 93.28 provides high classification accuracy comparing to other depths and for the fourth dataset depth, 94.78 presents better accuracy than others. In future work, we introduce the map reduce process before training which reduces the training time and also increase the accuracy rate in proposed system.

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