3.3.2 Number of books and chapters in edited volumes/books published and papers published in national/ international conference proceedings per teacher during year (2021-22)

S No.	Name of the teacher	Title of the book/chapters published	Title of the paper	Title of the proceedings of the conference	Name of the conference	National / International	Year of publication	ISBN/ISSN number of the proceeding
1	Dr.Shaik.Shakeer Basha	DEEP LEARNING AND ITS APPLICATIONS				International	2022	978-81-957614-4-9
2	Dr.Shaik.Shakeer Basha	CLOUD COMPUTING				International	2022	978-93-9187-85-5
3	JAYAPRADHA YELLAPRAGADA		Compensation Management and Employee Performance:Dairy Industries in Hyderabad	International Virtual Conference on Recent Trends in Engineering,Commerce, nagement,Humanities,Science and Enviromental Ecosystem for Sustainable Development	International Virtual Conference on Recent Trends in Engineering,Commerce, Management,Humanities,Science and Enviromental Ecosystem for Sustainable Development	International	2021	RFI/IVC/2021/ VITS-SSN/230
4	JAYAPRADHA YELLAPRAGADA		HumanResource Management in dairy industry :with reference to dairy units in hyderabad	international conference on multidisciplinary research and innovation in the field of engineering , commerce, management, humanities andscience	international conference on multidisciplinary research and innovation in the field of engineering , commerce, management, humanities andscience	International	2021	RFI/MR-2021/279
5	Jetty Bangaru Siddhartha		RDNN for classification and prediction of Rock/Mine in underwater acoustics	International Conference on Nanoelectronics, Nanophotonics, Nanomaterials, Nanobioscience & Nanotechnology.	International Conference on Nanoelectronics, Nanophotonics, Nanomaterials, Nanobioscience & Nanotechnology.	International	2021	2214-7853/ 2021
6	Vankayalapati Nagaraju		Deep learning binary fruit fly algorithm for identifying SYN flood attack from TCP/IP	International Conference on Nanoelectronics, Nanophotonics, Nanomaterials, Nanobioscience & Nanotechnology.	International Conference on Nanoelectronics, Nanophotonics, Nanomaterials, Nanobioscience & Nanotechnology.	International	2021	2214-7853/ 2021
7	Gurrala Chandrashekar		Side scan sonar image augmentation for sediment classification using deep learning based transfer learning approach	International Conference on Nanoelectronics, Nanophotonics, Nanomaterials, Nanobioscience & Nanotechnology.	International Conference on Nanoelectronics, Nanophotonics, Nanomaterials, Nanobioscience & Nanotechnology.	International	2021	2214-7853/ 2021

8	L Shiva Shankar		Convolution Neural Network (CNN) Based Computerized Classification of Adulterated Fruits with SIFT and Bag of words (BOW)	2022 4th International Conference on Smart Systems and Inventive Technology (ICSSIT)	2023 4th International Conference on Smart Systems and Inventive Technology (ICSSIT)	International	2022	9781-1-6654-0118-0
9	Alla Sravani		Convolution Neural Network (CNN) Based Computerized Classification of Adulterated Fruits with SIFT and Bag of words (BOW)	2023 4th International Conference on Smart Systems and Inventive Technology (ICSSIT)	2024 4th International Conference on Smart Systems and Inventive Technology (ICSSIT)	International	2022	9781-1-6654-0118-0
10	S. Rajender		Convolution Neural Network (CNN) Based Computerized Classification of Adulterated Fruits with SIFT and Bag of words (BOW)	2024 4th International Conference on Smart Systems and Inventive Technology (ICSSIT)	2025 4th International Conference on Smart Systems and Inventive Technology (ICSSIT)	International	2022	ISBN: 9781-1-6654-0118-0

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Technological Perspective of Fuzzy Logic System and its Applications

Dr. Syed Khasim, Dr. Shaik Shakeer Basha & Dr. Syed Khasim

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Abstract

Human instinct is very complex. Understanding this instinct requires strong dimensional analysis of discourse knowledge. Computer systems are now being trained to recognize how things work in a real-time environment for intelligent analysis. This attempt, although very advanced, has one limitation. There is an intelligence gap that puts humans one step ahead of machines. The fuzzy logic system can be used to make a machine better understand this intelligence gap. In other words, fuzzy logic is a computer intelligence technique that makes a computer understand and think like humans. The fuzzy logic system is now attracting scientists. and engineers around the world as it can tackle previously unsolved problems by integrating its capabilities with soft computing techniques such as neurological and chaos computing, genetic algorithms, probability calculus, and immune networks. improved knowledge-based technology or expert system, but also mainly the granularity of intelligence has changed. With the help of the fuzzy logic system, household appliance manufacturers today, for example, embed intelligence in certain products. The application of a fuzzy logic system also transformed industrial process control and enabled different approaches to product development. The fuzzy logic system has appeared mainly in America and Europe, with Japanese companies spearheading the commercialization of the technology. The aim of this study is twofold: first, to understand the fuzzy logic system for effective decision-making, and second, to demonstrate the existence of this intelligence gap through real-time examples. The examples are carefully chosen to illustrate and demonstrate the applications of the fuzzy logic system to any reader.

References

Keywords

Fuzzy Logic, Fuzzy Logic Technology, Fuzzy Logic System, Fuzzy Sets

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Compensation Management and Employee Performance: Dairy Industries in Hyderabad

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RDNN for classification and prediction of Rock/Mine in underwater acoustics

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ABSTRACT

The detection of minerals (mines) or rocks would have been extremely difficult without the expansion of the Sound Navigation Ranging methodology, which uses specific parameters to determine if a barrier or a surface is a mine or rock. Hence, this proposed work is concerned with the progression of distinctive among metal cylinder which is named as mines and cylindrical shape material which is named as rocks using deep learning based algorithms. Moreover, this work introduced novel technique as Rock or mine Detection Neural Network for performing rock/mine prediction and classification in underwater acoustics. The proposed RDNN method outperforms the outcomes by attaining high accuracy as 92.85% mean accuracy that makes better model performance.

Selection and peer-review under responsibility of the scientific committee of the International Conference on Nanoelectronics, Nanophotonics, Nanomaterials, Nanobioscience & Nanotechnology.

1. Introduction

One of the major difficult task in sonar targets are classification of substantial properties in underwater acoustics sonar objects such as mine like objects, rocks etc. By Jetty [1] applied various machine learning algorithms for identifying rocks/mines and distinguishing the same from underground data of unmanned vehicle. Here the neural networks are trained to distinguish the sonar based datasets into metal like mine, or rocks of comparable size. Khatik et al. [2] proposed generic rock mass rating for categorizing rocks using artificial neural network. Venkataraman Padmaja et al. [3] Machine learning techniques such as KNN, decision tree, and gradient booster, as well as SVM techniques, were used to separate the objects, such as rock or mine, in order to obtain high resolution images. Using a feature set and a Gradient Boosting classifier, this model achieves an accuracy of roughly 90%. Fig. 1 demonstrates finding abnormalities such as rocks which is classified from mine like objects in underwater acoustics system.

But, this paper focused on performing extra investigation in sonar dataset for detection and distinguishing the rocks or mines like materials in underwater acoustics using deep learning based neural network approach [32,33]. Moreover, comparison of network distinguishing performance of existing deep learning models along with our proposed neural network based layers by evaluating accuracy and loss measures as metrics evaluation.

2. Related work

Ravi et al. [9] introduced Online Multiple Kernel Learning (OMKL) is a combination of neural networks and online learning that tries to build a kernel-based prediction function from a pool of predefined kernels. Here, SVM and NN algorithms were applied to distinguish sonar data. Hassan et al. [4] utilize PCA and standalone architecture to integrate Back Propagation Neural Network for the categorization of two datasets (sonar and ionosphere datasets) in bagging ensemble architecture. Lee et al. [20] Due to the high density of fine floats or aquatic microorganisms, water bodies frequently show a serious reduction in visibility. Shin et al. [21] Because optical images have limitations, imaging sonar has become a generally accepted option for obtaining accurate measurements regardless of the turbidity of the water. Sejin Lee et al. [22] introduced image synthesizing method to capture sonar images using underwater simulator. Fenglei Han et al. [23] focused on real time underwater object detection and as well as classification using deep learning based CNN approach to attain underwater working operation. Simon Fong et al. [6] applied incremental data stream mining methodology with conflict analysis approach on underwater sonar signal detection to examine the efficiency. Chen

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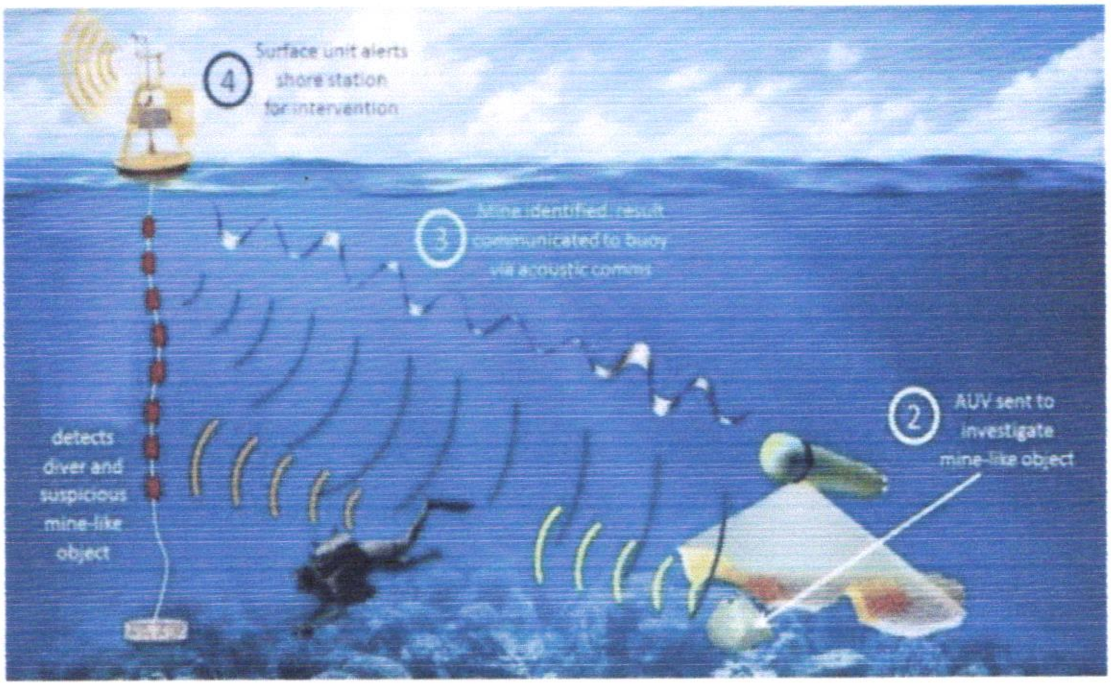

Fig. 1. Abnormality detection in underwater acoustics.

gyu Xie et al. [16] focused on predicting the rock size while blasting mine with greater accuracy and attained high consistency using artificial intelligence approach. Babaeian et al. [24] utilized regression model for finding the rock size as well as explained its dominance. Ding et al. [25] applied stochastic gradient boosting algorithm to categorize the stability of pillar in underwater mines. Ebrahimi et al. [26] developed Artificial Neural Network and Bee colony algorithm to offer suitable rock destruction for achieving higher accuracy using RMSE metric evaluation. Zhang et al. [27] presented an ANN based detection algorithm for an UAV (Unmanned Aerial Vehicle) based on slope and skewness of received signals in terms of error rate. Hao Yue et al. [18], Guojian Cheng et al. [17]underwater acoustics sonar targets were classified using deep learning based CNN approach attains 94.8% accuracy. G. Huo et al. [28] integration of both semi-synthetic data generation as well as deep learning based transfer learning approach provides more accuracy in categorizing underwater objects. Jongkwon Choi et al. [12] utilized machine learning algorithms such as random forest, CNN, SVM, feed forward neural network for categorizing surface or underwater acoustics in ocean via low frequency acoustic data. Nikitha et al. [29] and Harvinder Singh et al. [11] developed machine learning algorithms for distinguishing rocks or mines in underwater using highly spatial dataset. Mukherjee et al. [10] introduced pattern analysis algorithm which constructs both symbolic dynamic and finite automata theory for finding mine like objects in underwater acoustics surroundings. Bradley Efron et al. [19] explained how the LAR model were derived the properties that constrains the sum of the absolute regression coefficients. Abhishek et al. [30] utilized Fast Region CNN approach to categorize the underwater objects as rocks or mines. Ritwick Ghosh et al. [7] determined that machine learning techniques and neural network algorithms by Abdul-Qader et al. [13] support vector machine algorithm by Jade et al. [9], deep learning based network [5,8] attained better outcomes in classifying rocks or mines using sonar dataset. Dhiraj Neupane et al. [31] and Bouzerdoum et al. [14] studied deep learning based approaches and machine learning algorithms by Dahee Jung et al. [15] for detecting sonar mine objects using sonar images.

3. Proposed workflow

The proposed workflow describes the classification of rock or mine in underwater acoustics through sonar technology.

Step 1: Gathering dataset from the specified repository especially SONAR dataset.

Step 2: Loading the dataset for training phase.

Step 3: Apply feature extraction technique to extract the relevant features related with sonar dataset.

Step 4: Create RDNN algorithm for predicting and categorizing the sonar dataset as normal (mine) and abnormal (rock) in underwater acoustics.

Step 5: Compute the central measures tendency for mean and standard deviation.

Step 6: Splitting the dataset as training and testing with 70%, 30% respectively

Step 7: Calculate metrics such as accuracy, loss, accuracy based on validation and validation loss for evaluating the overall performance of the model.

4. Dataset explanation

The dataset which were utilized in this work have been taken from the resource namely UCI machine learning repository described in Table 1. This high generalization has been attained on the Neural Network based approach. To achieve greater accuracy for performance enhancement, the implementation was done in Python version 3.7 environments. The resource link is mentioned as https://datahub.io/machine-learning/sonar#resource-sonar [34–35].

Table 1
Sonar dataset used in this proposed work.

Total	Mine	Rock
208	111	97

The total number of sonar data available in the source is 208. Among these data, 111 data allotted for mine metal, and the remaining 97 data allotted for rock material.

4.1. Data visualization

Keras also has a function for creating a visualization of the network neural network graph, which can help with more complex models. To create a plot in the network, plot_model () function is utilized. This function needs some parameters:

To_file (): name of the file to which to save the plot

Show_shapes (): shows the every layer as output shapes.

Show_layer_names (): show the layer names in the neural network.

RDNN model: our novel model to predict and classify the objects as mines or rocks

```
from keras.models import Sequential
  from keras.layers import Dense
  from keras.utils.vis_utils import plot_model
  model = Sequential()
  model.add(Dense(2, input_dim = 1, activation='relu'))
  model.add(Dense(1, activation='sigmoid'))
  plot_model(model, to_file='model_plot.png',
  show_shapes = True, show_layer_names = True)
```

4.2. Density curve

Density curve is utilized for visualizing the reliable and informative data. This curve provides a variety of alternatives for viewing a single variable from one or more categories. The histogram plot using density curve is depicted in Fig. 2.

Fig. 2. Histogram plot using Density curve.

4.3. Data correlation

The statistics of data is implemented using heatmap. The heat map is a two-dimensional representation of the data. In the graph, the data values are represented by colors. The purpose of a heat map is to create a colorful visual summary of data. For each value to be plotted, a heat map has values indicating several shades of the same color. The darker hues of the chart usually correspond to higher values than the lighter colors. A completely different color can likewise be utilized for a significantly different value. By using matplotlib, the output of heat map will displayed as shown in Fig. 3.

4.4. Feature selection

Feature selection is a much more straightforward task that is given a list of prospective features, choose a few and eliminate the rest. Feature selection is used to avoid redundancy and/or irrelevancy in features, as well as to limit the number of features available to avoid over-fitting.

4.4.1. Least Angle Regression(LAR)

A novel model selection approach called Least Angle Regression is a helpful and less greedy alternative of previous forward selection methods shown in Fig. 4.It is fast and very efficient method for fitting a Lasso regularized regression model without using hyper parameters. This regression provides the following

i. An alternating way to train Lasso regularized linear regression approach which adds penalty to loss function during training phase.
ii. The prediction of rock or mine can be done by evaluating LAR regression model.
iii. The configuration of LARS regression model for a novel sonar mine rock detection automatically through k-fold validation technique.

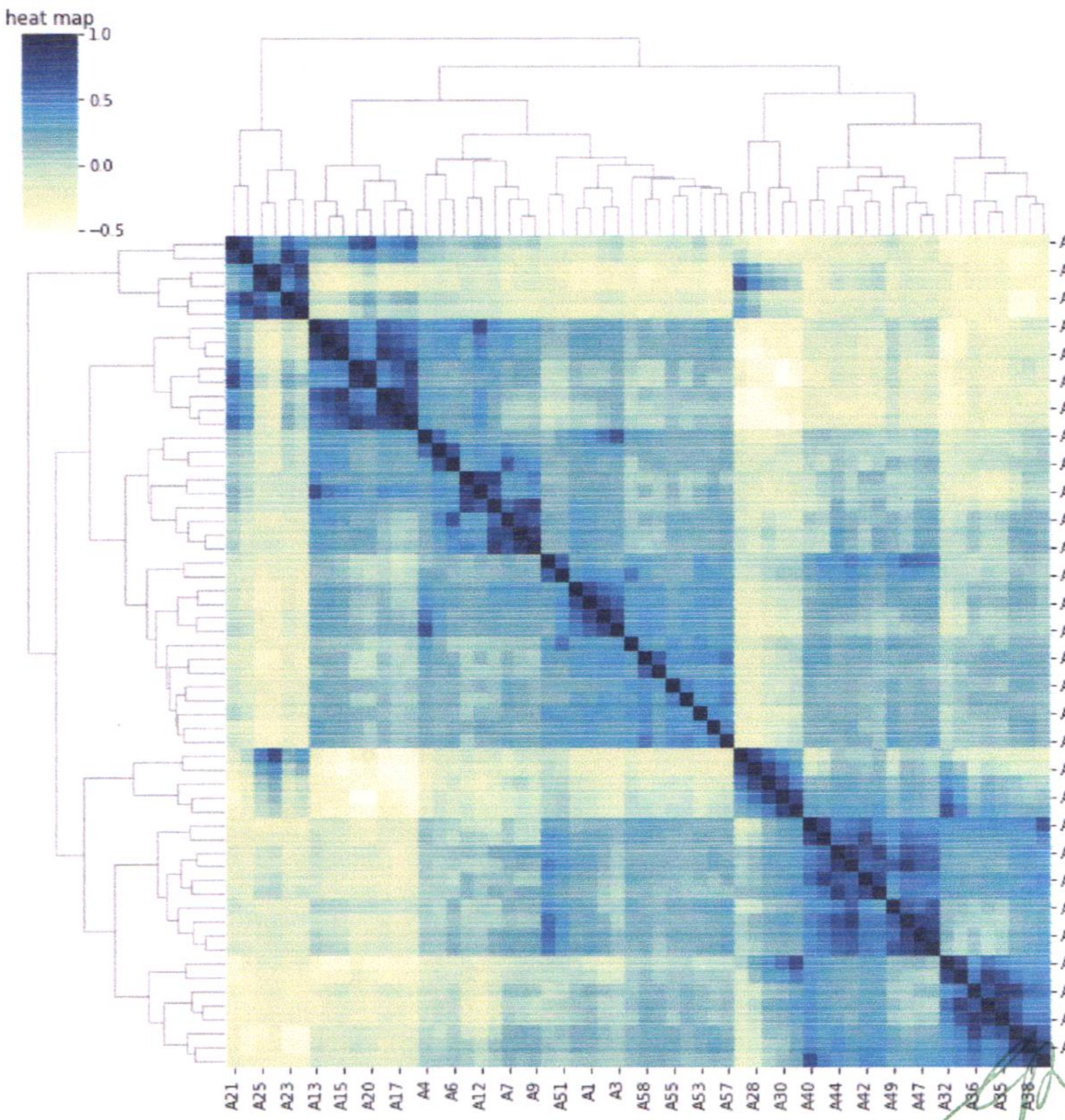

Fig. 3. Histogram for visualizing data using Heat map.

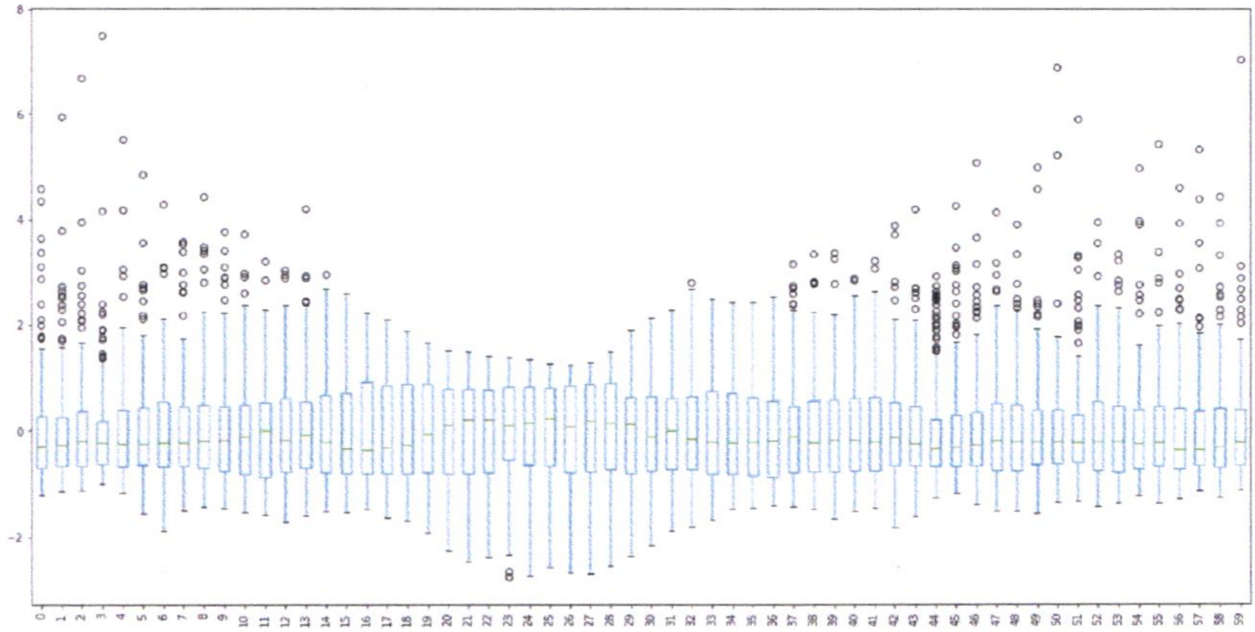

Fig. 4. LAR regression model for feature selection.

5. Proposed architecture

The architecture elucidates about how we are predicting the metal like mine objects, rocks etc and distinguishing the sonar abnormal data into rocks or mines using RDNN classifier model. The proposed framework is depicted in Fig. 5.

The sonar abnormal dataset have been collected from Kaggle website as a source for this work. When the features in the data have diverse ranges, normalization is a strategy used during data preparation to adjust the values of numeric columns in a dataset to use a common scale. Feature extraction is utilized to recognize essential features in the dataset for coding by deriving new datas from the original dataset. A technique for natural language processing that extracts and categorizes the parameters used in a sentence, document, webpage, and so on. Then, split the sonar abnormal datasets into training data and testing datato train and test the model for measuring the accuracy of the neural network model. Now we applied Rock/mine detection based neural network classifier model to make prediction of underwater acoustics objects also distinguishing the objects into mines and rocks.

6. Metrics evaluation

A. Central tendency measures

Each layer's activation may result in a different data distribution. As a result, we must normalize the data input to each layer by subtracting the mean and dividing by the standard deviation to improve the stability of deep neural networks. In this method we are estimating the central tendency measures such as mean and standard deviation to enhance the steadiness of neural networks for improving the overall performance. Mean and SD formula along with its description are mentioned in Table 2.

Table 2
Central tendency measures.

Central Tendency Measures		
Appraise	Modus operandi	Depiction
Mean	$\Sigma x/n$	Average of list of given numbers.
SD	$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2}$	Measures the dispersion of sonar dataset relative to its mean values

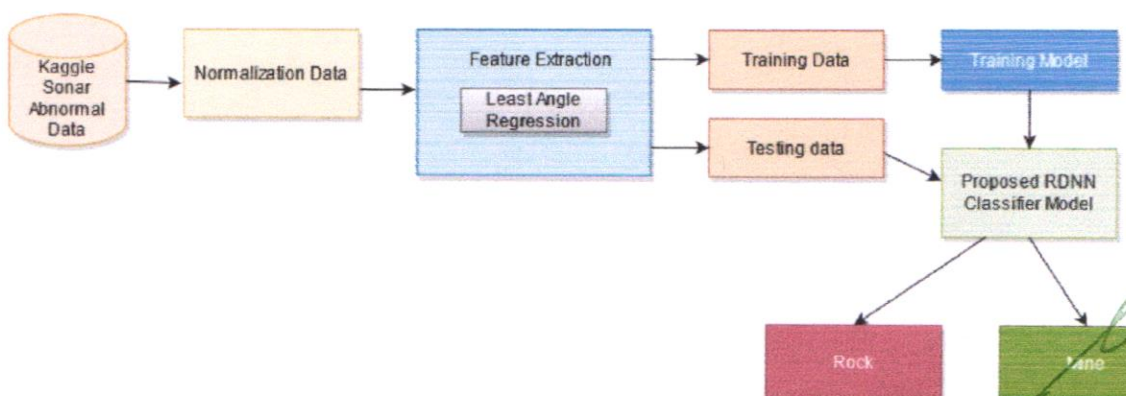

Fig. 5. Proposed architecture for classifying underwater objects as mines or rocks.

B. Metrics Estimation

The metrics such as accuracy, loss, validation loss and validation accuracy were estimated for identifying underwater acoustics objects and classifying the sonar data as rock or mine.

i. *Accuracy*: Accuracy is defined as the number of correctly classified data from total number of input sonar abnormal data which makes greater enhancement in predicting NN model performance in mine like objects detection. The formula used to measure accuracy is shown in Eq. (1).

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

ii. *Epoch*: An epoch is a unit of time used to train a neural network with all of the training data for a single cycle. We use all of the data exactly once in an epoch. A forward and backward pass are combined to make one pass: An epoch is made up of one or more batches in which we train the neural network using a portion of the dataset.
iii. *Validation Accuracy:* The validation accuracy is predicted by contrasting the index of the highest scoring class in y label prediction vector and the index of the actual class in the y label true vector. It returns 0 or 1. The accuracy is predicted by correctly classified data among all input sonar abnormal datasets.
iv. *Loss:*The loss functions are supportive to train RDNN especially Adam optimizer model. Based on actual input and predicted input datas the losses will be estimated (i. e) distinguish among output data and target datas from sonar abnormal datasets. We introduced loss function (L_{segm}) which is the integration of weighted loss (L_w) IoU and also weighted binary cross entropy L_w BCE loss for every segmentation of sonar data. The formula for loss functions as shown in Eq. (2).

$$L_{segm} = L_w IoU + \lambda L_w BCE \tag{2}$$

where λ represents weight of abnormal data.

v. *Validation Loss:* The loss function is validated by distinguishing among sonar mine or rock from underwater acoustics sonar data for segmenting sonar data into normal data as mineabnormal data as rock exactly.

7. Experimental outcomes

The layers utilized for sonar abnormal dataset using deep learning neural network based Rock/mine detection and classification. The layers maintained by models, the size of layers, input shape, activation layer and which optimizers are utilized by various existing models and comparing with proposed approach depicted in Table 3.

7.1. Accuracy comparison

The mean accuracy are evaluated to estimate the performance of RDNN model in predicting and distinguishing rock or mine in underwater acoustics using sonar dataset. Fig. 6 demonstrates validation accuracy as 85.7% accuracy as 100% loss as 0.04 validation loss as 0.35 in prediction and distinguishing underwater objects like mine or rocks using sonar dataset using k-fold cross validation with 50 epochs for model 1.

Fig. 7 demonstrates validation accuracy of 90.48% accuracy as 98.2% loss as 0.13 validation loss as 0.287 in prediction and distinguishing underwater objects like mine or rocks using sonar dataset using k-fold cross validation with 50 epochs for model 2.

Fig. 8 demonstrates validation accuracy as 85.7% accuracy as 100% loss as 0.13 validation loss as 0.518 in prediction and distinguishing underwater objects like mine or rocks using sonar dataset using k-fold cross validation with 50 epochs for model 3.

Fig. 9 demonstrates validation accuracy as 92.8% accuracy as 100% loss as 0.33 validation loss as 0.39 in prediction and distinguishing underwater objects like mine or rocks using sonar dataset for novel proposed RDNN model using 50 epochs.

7.2. Overall comparison

Here, model 1, 2 and 3 are the pre trained model with splitting of training and testing data including prediction as well as classifi-

Table 3
Proposed RDNN model for Sonar Abnormal dataset.

Layer	Layer size	Input Shape	Activation	Optimizer
Model1	Dense(100)	60	ReLU	Adam
Model2	Dense(30)	60	ReLU	Adam
Model3	Dense(60),Dense(60)	60	ReLU	Adam
Proposed RDNN Model	Dense(60)	60	ReLU	Adam

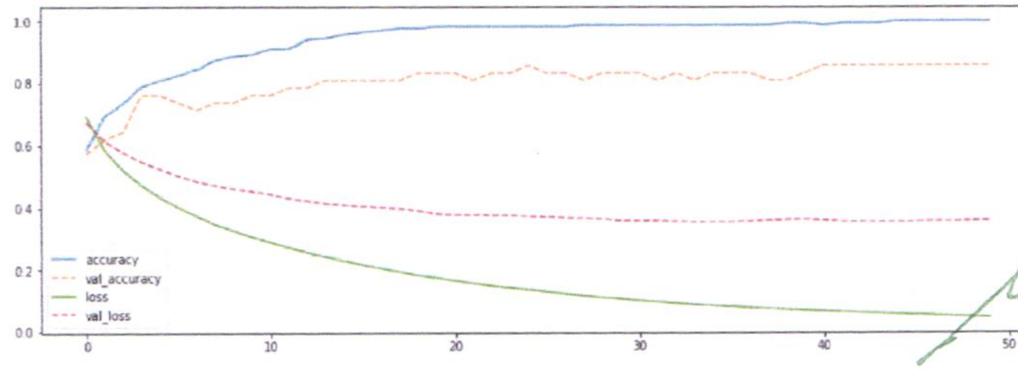

Fig. 6. Estimating metrics such as accuracy, validation accuracy, loss and validation loss for model1.

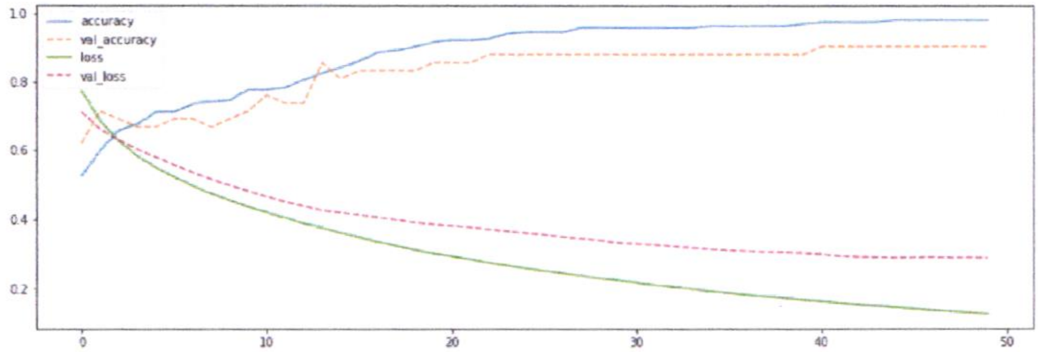

Fig. 7. Estimating metrics such as accuracy, validation accuracy, loss and validation loss for model2.

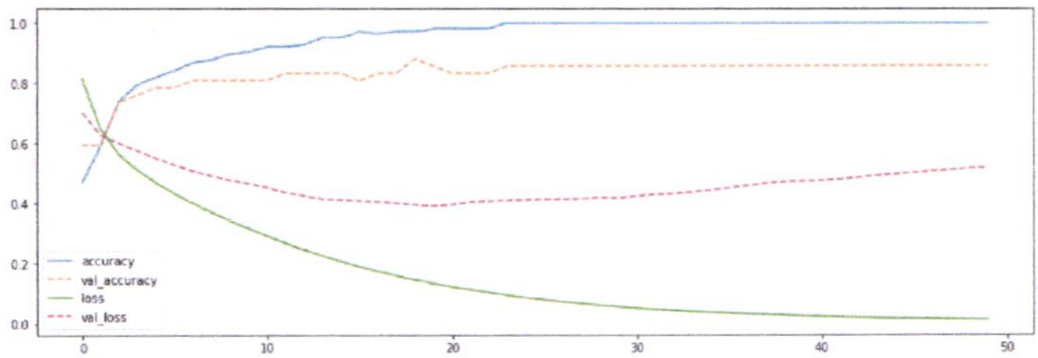

Fig. 8. Estimating metrics such as accuracy, validation accuracy, loss and validation loss for model3.

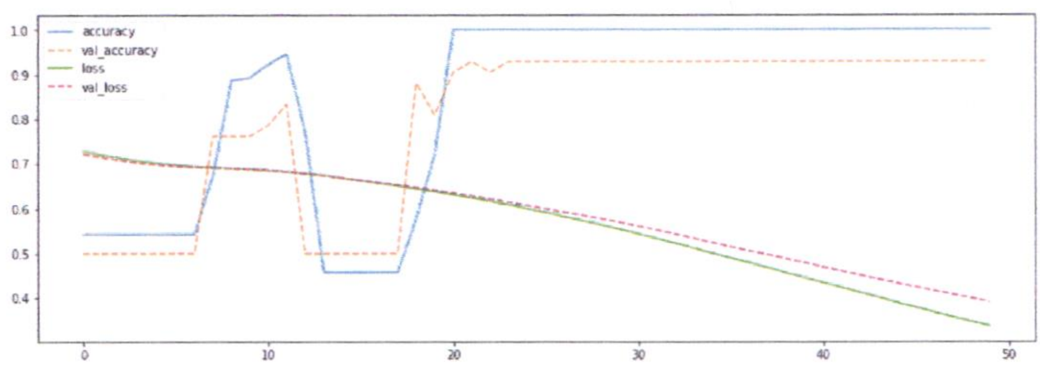

Fig. 9. Estimating metrics such as accuracy, validation accuracy, loss and validation loss for RDNN proposed model.

cation of underground objects as mines or rocks. While comparing with existing models, this RDNN model generates better mean accuracy as 100% with 0% Standard Deviation in prediction and also classification of objects achieves 92.85%. The overall comparison on prediction and classifying rocks or mines using sonar dataset is described in Table 4.

Table 4
Overall comparison among models.

Model	Training	Testing	K-fold Evaluation	Prediction
Model1	100	85.7	88.57 for mean 9.1% SD	90.47
Model2	98.84	90.48	82.57 for mean 7.63 for SD	90.47
Model3	100	85.7	84.41 for mean 9.95 for SD	88.09
Proposed Model(RDNN)	100	92.86	100 for mean 0.00 for SD	92.85

8. Conclusion

In this proposed work, RDNN classifier model have been applied for metal classifying namely rock or mine in underwater acoustics through statistical analysis in deep learning based neural networks using sonar datasets. Sonar technology combined with an unmanned autonomous vehicle can be used to remove signals in underwater communication. But, here Rock/mine detection neural network approach reveals enhanced outcomes by achieving mean accuracy of 100% with 0% SD using k-fold evaluation and sonar prediction achieves 92.85% to enhance the model performance. To achieve more prediction accuracy, the hyper parameters has to be done in sonar dataset for better classification of objects like mine/rocks in underwater acoustics.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] J.B. Siddhartha, T. Jaya, V. Rajendran, Distinguished study of various materials like metal mine/rock from underground data of unmanned vehicle using machine learning, Int. J. Grid Distrib. Comput. 13 (2) (2020) 574–583.
[2] V.M. Khatik, A.K. Nandi, A generic method for rock mass classification, J. Rock Mech. Geotech. Eng. 100 (1) (2018) 102–116, https://doi.org/10.1016/j.jrmge.2017.09.007, ISSN 1674-7755.
[3] V. Padmaja, V. Rajendran, P. Vijayalakshmi, Study on metal mine detection from underwater sonar images using data mining and machine learning techniques, J. Ambient Intell. Hum. Comput. 12 (2) (2020).
[4] H.T. Hassan, M.U. Khalid, K. Imran, Intelligent object and pattern recognition using ensembles in back propagation neural network, Int. J. Elect. Comput. Sci., IJECS-IJENS 10 (06) (2010).
[5] M. Sung, J. Kim, M. Lee, B. Kim, T. Kim, J. Kim, S.-C. Yu, Realistic sonar image simulation using deep learning for underwater object detection, Int. J. Control Autom. Syst. 18 (2020) 523–534, https://doi.org/10.1007/s12555-019-0691-3.
[6] S. Fong, S. Deb, R. Wong, G. Sun, Underwater sonar signals recognition by incremental data stream mining with conflict analysis, Int. J. Distrib. Sens. Netw. (5) (2014) 1–12, https://doi.org/10.1155/2014/635834.
[7] R. Ghosh, Sonar target classification problem: machine learning models, Int. J. Sci. Res. 9 (1) (2020) 247–248.
[8] A. Galusha, J. Dale, J.M. Keller, A. Zare, Deep convolutional neural network target classification for underwater synthetic aperture sonar imagery, in: Proc. SPIE 11012, Detection and Sensing of Mines, Explosive Objects, and Obscured Targets XXIV, Volume 11012, Issue 05 (10 May 2019). doi: 10.1117/12.2519521.
[9] R.K. Jade, L.K. Verma, K. Verma, Classification using neural network & support vector machine for sonar dataset, Int. J. Comput. Trends Technol. 4 (2) (2013) 116–119, ISSN: 2231-2803.
[10] K. Mukherjee, S. Gupta, A. Ray, S. Phoha, Symbolic analysis of sonar data for underwater target detection, IEEE J. Oceanic Eng. 36 (2) (2011) 219–230.
[11] H. Singh, N. Hooda, Prediction of underwater surface target through SONAR: a case-study of machine learning, Journal of Emerging Technologies and Innovative Research JETIR 6 (6) (2019) 159–164 (ISSN-2349-5162).
[12] J. Choi, Y. Choo, K. Lee, Acoustic classification of surface and underwater vessels in the ocean using supervised machine learning, Sensors 19 (16) (2019), https://doi.org/10.3390/s19163492.
[13] B. Abdul-Qader, Techniques for classification sonar: rocks vs. mines, Int. J. Sci. Eng. Res. 7 (11) (2016) 883–903.
[14] A. Bouzerdouma, P.B. Chappleb, M. Drasc, Y. Guod, L. Hameyc, T. Hassanzadehc, T. Hoang Lea, O. Mohamad Nezamic, M. Orgunc, S.Lam Phunga, C. Ritza, M. Shahpasandc, Improved deep-learning-based classification of mine like contacts in sonar images from autonomous underwater vehicles, in: Underwater Acoustics Conference and Exhibition UACE2019 Conference Proceedings, ISSN- 2408-0195, pp.179-186.
[15] A. Prabhakaran, K.S. Krishnan, R. Dhinakaran, S. Baskar, V.S. Shaisundaram, Analysis of the efficiency of an automotive alternator by replacing mild steel into aluminum as a material for rotor, Mater. Today:. Proc. 37 (2021) 1269–1273.
[16] D. Jung, Y. Choi, Systematic review of machine learning applications in mining: exploration, exploitation, and reclamation, Minerals 11 (2021) 148, https://doi.org/10.3390/min11020148.
[17] C. Xie, H. Nguyen, X.-N. Bui, Y. Choi, J. Zhou, T. Nguyen-Trang, Predicting rock size distribution in mine blasting using various novel soft computing models based on meta-heuristics and machine learning algorithms, Geosci. Front. 12 (3) (2021), https://doi.org/10.1016/j.gsf.2020.11.005, ISSN 1674-9871.
[18] G. Cheng, W. Guo, 2017 IOP Conf. Series: Journal of Physics: Conf. Series 887 (2017) 012089, ISAI2017. doi: 10.1088/1742-6596/887/1/012089.
[19] H. Yue, L. Zhang, D. Wang, Y. Wang, Z. Lu, The Classification of Underwater Acoustic Targets Based on Deep Learning Methods, in: 2nd International Conference on Control, Automation, and Artificial Intelligence (CAAI 2017), Advances in Intelligent Systems Research 134 (2017) 526–529.
[20] B. Efron, T. Hastie, I. Johnstone, R. Tibshirani, Least angle regression, Ann. Stat. 32 (2) (2004) 407–499.
[21] S. Lee, Deep learning of submerged body images from 2d sonar sensor based on convolutional neural network, in Underwater Technology (UT), 2017 IEEE, 2017, pp. 1–3.
[22] Y.-S. Shin, Y. Lee, H.-T. Choi, and A. Kim, Bundle adjustment from sonar images and SLAM application for seafloor mapping, in: Proceedings of the IEEE/MTS OCEANS Conference and Exhibition, Washington, DC, Oct. 2015, pp. 1–6.
[23] S. Lee, B. Park, A. Kim, Deep Learning from Shallow Dives:Sonar Image Generation and Training for Underwater Object Detection, 2018, pp. 1-8.
[24] S.T. Prabakaran, P. Sakthivel, M. Shanmugam, S. Satish, M. Muniyappan, V.S. Shaisundaram, Modelling and experimental validation of TIG welding of INCONEL 718, Mater. Today:. Proc. 37 (2021) 1917–1931.
[25] F. Han, J. Yao, H. Zhu, C. Wang, Underwater Image Processing and Object Detection Based on Deep CNN Method, J. Sens. 9: 1-20. doi: 10.1155/2020/6707328. Article ID 6707328.
[26] M. Babaeian, M. Ataei, F. Sereshki, F. Sotoudeh, S. Mohammadi, A new framework for evaluation of rock fragmentation in open pitmines, J. Rock Mech. Geotech. Eng. 11 (2) (2019) 325–336.
[27] H. Ding, G. Li, X. Dong, Y. Lin, Prediction of pillar stability for underground mines using the stochastic gradient boosting technique, IEEE Access 6 (2018) 69253–69264.
[28] E. Ebrahimi, M. Monjezi, M.R. Khalesi, D.J. Armaghani, Prediction and optimization of back-break and rock fragmentation using an artificial neural network and a bee colony algorithm, Bull. Eng. Geol. Environ. 75 (1) (2016) 27–36.
[29] H. Zhang, C. Cao, L. Xu, T.A. Gulliver, A UAV detection algorithm based on an artificial neural network, IEEE Access 6 (2018) 24720–24728.
[30] G. Huo, Z. Wu, J. Li, Underwater object classification in sidescan sonar images using deep transfer learning and semisynthetic training data, IEEE Access 8 (2020) 47407–47418, https://doi.org/10.1109/ACCESS.2020.2978880.
[31] S. Satish, S.J. Alexis, A. Bhuvendran, M. Shanmugam, S. Baskar, V.S. Shaisundaram, Design and analysis of mild steel mini truck body for increasing the payload capacity, Mater. Today:. Proc. 37 (2021) 1274–1280.
[32] T. Nikitha, B. Hadhvika, K. Vaidehi, Prediction of underwater surface target through SONAR by using machine learning algorithms, JETIR 6 (6) (2019) 159–164.
[33] D. Neupane, J. Seok, A review on deep learning-based approaches for automatic sonar target recognition, Electronics 9 (11) (2020) 1972, https://doi.org/10.3390/electronics9111972.
[34] E.N. Ganesh, V. Rajendran, D. Ravikumar, P. SaiKumar, G. Revathy, P. Harivardhan, Remote sensing analysis framework for maritime surveillance application, Int. J. Oceans Oceanogr. 15 (1) (2021) 11–17, ISSN 0973-2667.
[35] E.N. Ganesh, V. Rajendran, D. Ravikumar, P. Sai Kumar, G. Revathy, P. Harivardhan, Detection and route estimation of ship vessels using linear filtering and ARMA Model from AIS Data, Int. J. Oceans Oceanogr. 15 (1) (2021) 1–10, ISSN 0973-2667.

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Deep learning binary fruit fly algorithm for identifying SYN flood attack from TCP/IP

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ABSTRACT

SYN Flood Attack is one form of distributed denial of service attack that attains the handshake process of TCP. This attack consumes all available server resources and provokes legitimate traffic which aims to make the server unavailable. It causes serious damage to cloud server and networking protocols. The main objective of this research work is to train the neural network for detecting the attack and to secure network connection. A novel binary fruit fly optimization algorithm with deep learning is proposed to predict the syn flood attack. The proposed algorithm is implemented using the KDD cup dataset. DL-BFFA algorithm has achieved 99.96% detection accuracy for detecting the SYN Flood Attack. A comparison study is conducted to validate the proposed model.

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1. Introduction

Nowadays the internet offers online banking, e-commerce, and education services online. SYN flood attack is a type of cyber threat that can affect the internet services such as email, online accounting, and public networking. This attack occurs, and then the users aren't able to access network resources, devices, and information systems. SYN flood attack is a method to create a connection between the client and server in a transmission control protocol TCP/IP network. It can occupy the available connections in the port and leaves an incomplete handshake. The send request will be continued by an attacker until all open ports are saturated with their requests. It has denied the connection to the legitimate users in the network. In the big data field, this type of attack is increased due to political, e-commercial, and personal reasons. The main target of this attack is to harm web-based applications, media, and software industries. The schematic example of an SYN flood attack on the network is shown in Fig. 1.

In 1994, SYN flood attacks were discovered by Bill Cheswick and Steve Bellovin. CERT published an article for mitigating SYN flood attacks [1]. It is very crucial for secure communication in the network. The traditional approaches are mainly focused on manual recognition and statistical analysis. New techniques are based on data mining, machine learning, and neural networking. Entropy-based lightweight DDOS flood attack detection model has achieved fine anomaly detection accuracy [2]. In a network security system, a software-defined network (SDN) is deployed using programming languages such as java and python with security functionality methods [3–5]. A TCP connection initiated using a three-way handshake technique has led to vulnerability to the attack [6]. In 2018, Kaspersky has revealed that 50% of the cyber attack is based on the TCP SYN attack only [7].

Most of the research work focuses on the detection approaches are based on offline analysis and simulation methods such as patterns during normal and attack states, network traffic characteristics. Due to this limitation, the authors propose a deep learning-based model to predict the SYN flood attack in real-time. The main contribution of this is as follows.

- A novel binary fruit fly optimization algorithm with deep learning is proposed to predict the syn flood attack.
- Train the neural network model for detecting the attack to secure network connection.

This research paper is organized as follows: Section 2 addresses the detection and mitigation solution for SYN flood attacks. Section 3 discusses the data collection and feature selection techniques. The proposed BFFA model implementation details are

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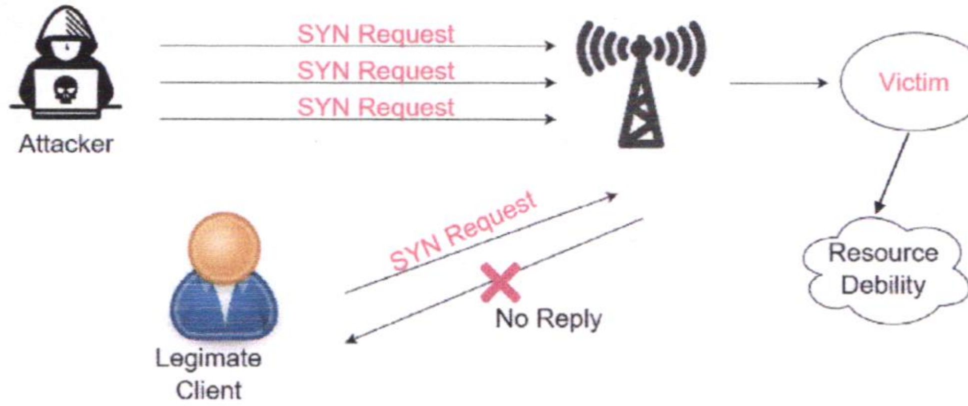

Fig 1. Schematic diagram of SYN flood Attack.

described in section 4. The performance analysis and the results are presented in section 5. Section 6 concludes the model and future work to carry out the reproductively of the model [23–25].

2. Related work

Many researchers have produced solutions for DDOS detection using static-based and machine learning-based approaches. The authors have proposed a novel deep learning model combined with the optimization algorithm to detect the SYN flood attack. Research works related to the statistical and machine learning models are discussed as follows:

2.1. Statistical analysis

The severities of the attacks are classified as TCP-ACK, Slowloris, and SYN attacks. The authors have determined the confidence interval and distribution of the network data during a normal time (without attack). Any deviation in the mean throughput value indicates the attack. The value of the mean throughput and confidence levels were used to detect the anomaly attack [8]. At early stages, the network attack was detected using the entropy property. It measures the close probability of new incoming packets concerning the total number of events. If the host receives an excess number of incoming packets then the entropy level drops and the randomness of the packet level decreases. The attacks are detected based on the experimental threshold values [9]. Open Flow table contains the copy of the packet number with flow entry. An entropy-based lightweight DDOS attack reduces the flow collection overhead. This model was implemented in software-defined networks and programmable switches [10]. The statistical analysis has overhead in the form of delay and high-speed network traffic.

2.2. Machine learning methods

Machine learning algorithms are used to detect and predict DDoS attacks. In SDN, the most common threats are DDOS attacks and intrusion. The authors have built the machine learning model based on the training data set. Machine learning algorithms such as support vector machines, neural networks, and fuzzy logic are applied to mitigate the attacks [11]. The authors of [12] have presented six machine learning approaches to analyze the DDOS attack. They have proved that a support vector machine predicts the attack with good accuracy and a low false-positive rate. An Artificial Neural Network and Naive Bayes models are used to detect the attack [13] in the network. Some of the research works have focused on a combination of two approaches. Traffic flow features are extracted using statistical analysis and apply machine learning algorithms to classify the anomaly attacks [14]. Different types of network attacks are detected with the help of data mining and machine learning techniques [18]. An intelligent bee colony algorithm was proposed by [19] for detecting the DDoS attack and traffic reduction algorithm to reduce the network traffic in the system.

3. Proposed methodology

The proposed Binary Fruit Fly Algorithm (BFFA) with deep learning model analyses the syn flood attacks and the network traffic. This model comprises data collection, feature extraction, input layer, dense layer, and output layer. Fig. 2, Depicts the architecture of the BFFA model to detect the attacks in the network.

3.1. Data collection

The authors have implemented the model on the KDD cup dataset. The KDD cup dataset was created by Stelfo et al., [15] based on the information captured from the DARPA98 IDS evaluation program. Table 1 describes the training and testing split of the two datasets. The BFFA model is trained with a 70%-30% data split.

In the preprocessing phase, the data is cleaned to extract useful information from the dataset. It can consist of normalization and feature extraction. Step to process the data are as follows

Step 1: Network traffic is defined as $N = [n_1, n_2, \ldots\ldots\ldots, n_n]$ where n_i is the original features of the input vector.

Step 2: T_n be a feature vector of transformed features of the dimension.

3.2. Feature extraction

This data consists of 4,900,000 single connection vectors with 41 features. The data is classified as normal or attacks. The attacks are categorized as Denial of Service (DOS), Remote to Local attack (R2L), User to Root attack (U2R), and Probing attack. The benchmark dataset is downloaded from the following link [16]. Fig. 3. Illustrates the covariance of certain selected features extracted from the data set. KDD cup features are divided into three groups such as basic features, content features, and traffic features. Basic features can be extracted from the TCP/IP connection and it leads to an implicit delay in detection. Content features are selected from the suspicious behavior in the data. Traffic features are computed for window intervals from the same host and same service. All the important features are extracted from the data based on priority. In KDD cup data, eight important features are identified such as

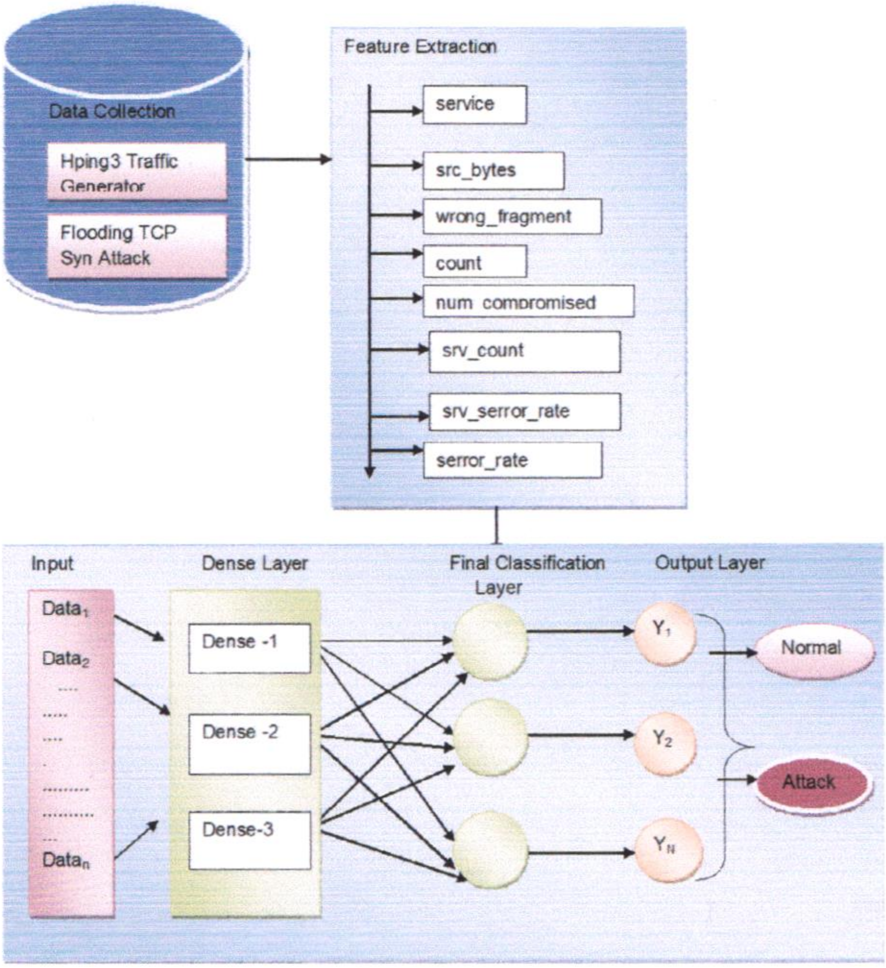

Fig 2. Architecture of the proposed model.

Table 1
Statics of training and testing data.

Data	Total	Training	Testing
KDDcup	18,230	12,761	5469

server, src_bytes, count, srv_count, and serror_rate. Three features of the dataset have zero values. To avoid over fitting the features of wrong_fragment, num_comprised and srv_serror_rate are nullified.

3.3. Input layer

This is the first layer of the proposed model which consists of artificial input neurons. It collects the data and sends it to subsequent layers for weight calculation. Each input layer has its weights and multiplies the incoming input data for further process.

3.4. Dense layer

The neural network layer is connected deeply in the network. It receives input from the input layer then performs matrix multiplication. The matrix vector contains values that can be trained and

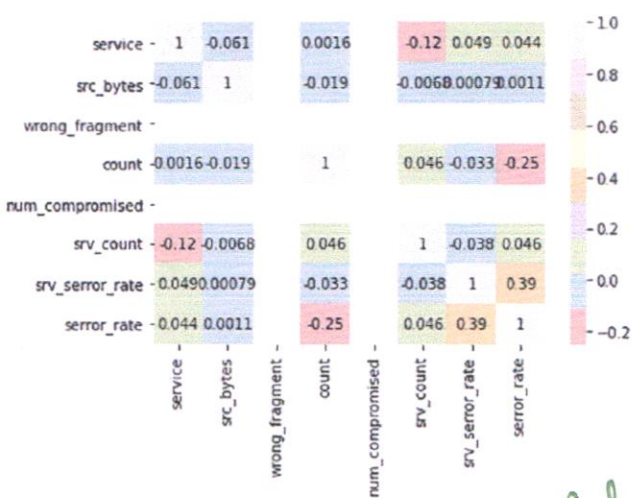

Fig 3. Covariance of selected Feature for KDD99 data.

updated with the help of back propagation. Our model is trained using the parameters such as units, activation, initializes, and input dimensions.

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3.5. Output layer

The fully connected output layer has a single neuron and acts as a classifier. The hyper parameters of the activation function and learning rate are set based on the optimization algorithm. The output layer is set the sigmoid activation function and learning rate (0.00174) to implement the models. The model to classify the attacks in the network, into two classes as normal or attack based on the learning process. See (Table 2).

3.6. Proposed BIFFA algorithm

Binary Fruit Fly Algorithm (BFFA) is used to solve discrete optimization problems. It consists of two phases such as smell phase and the visit phase. Our proposed deep learning model is based on the [17] vision function. This function is used for improving the classification results. The BFFA model has the following steps

1. Adjust the parameters.
2. Initialize the fruit flies randomly.
3. Calculate the visit phase value for every fruit fly as
4. $Visit_i$ = Function (v_i).
5. Find the best visit value and fix the layer in that value for the next iterations

[Best Visit] = Max [Visit]

This algorithm is used for initializing the parameters in deep learning models. To train our proposed deep learning experiment to obtain the optimal parameters are shown in Table 3. Our proposed BFFA algorithm performs well for detecting the attacks as compared to other optimized algorithms. Binary fruit fly algorithms can classify the normal and attacks. BFFA algorithm combines the swarm intelligence optimizes technique for setting the parameters in deep learning neural networks. This approach can reduce the learning parameter for designing the network and is optimized for all syn flood datasets.

Table 4 shows the deep learning models input and output layer concerning the parameters. The main components of the BFFA model are described as follows: initialize the hyper parameter, evaluate the solution and find a new solution for tuning the parameters. The dense layer is activated with the relu function. The classifier uses binary cross entropy for detecting the attacks.

4. Experimental results and discussion

The BFFA model is implemented using a python programming language. The packages such as NumPy, sklearn, pickle, tqdm, pandas, sea born and matplotlib are used to implement the model. It is carried out by the two datasets KDD cup. This dataset has 41 features and is grouped into three categories such as content, traffic, and intrinsic features. The model performance is evaluated using accuracy metrics.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (1)$$

where,

True-positive (TP) = Number of data correctly predicts an attack.

False-positive (FP) = Number of data wrongly predicts normal.

True-negative(TN) = Number of data correctly predicts an attack.

False-negative (FN) = Number of data wrongly predicts normal.

Table 4
Proposed BFFA model.

Input: Two datasets as DS, Label C as classes of the attack
Output: Prediction of attacks
Initialize: Train-Test split
Epoch
Hyper parameters for firefly model

Training:
Step 1: $model_{seq}$ - -> Input and Output layers
Step 2: model $_{dense}$- ->(units, activation, kernal_initializers)
Step 3 : model $_{dense}$ - -> (number of classes, activation, kernal_initializers)
Step 4: model $_{compile}$ - -> (loss,optimizer, metrics)
Step 5: model $_{classifier}$ (BFFA_best_model())

4.1. Syn network model

This model is implemented using two fully connected dense layers. Dense layer parameters are output shape and activation function. This model has an output array of shapes as 32 with relu activation function. Training-testing split is 70–30 split. Syn network model is compiled with adam optimizer. The classifier uses a binary cross-entropy metric to predict two labels as normal or attack. This model is iterated for 10 epochs and produces 98% detect accuracy for KDD cup data.

4.2. TDLHBA (tuning deep learning using hybrid bat algorithm)

This algorithm combines the swarm intelligence algorithm for setting the parameters in deep learning neural networks. This approach can reduce the manual search of the learning parameters in the network. This approach is optimized for different datasets. This model is implemented on 40 neurons with relu activation function. This model achieves 99% accuracy for the dataset.

4.3. BBA (binary bat Algorithm)

The authors of Deep Dense [20] utilize the BBA model; it combines the Bi-LSTM with a dense layer to predict the attacks. The Bi-LSTM utilizes the 64 filters with tanh activation and L2 kernel regularizer. This model is compiled using the relu activation function.

4.4. DL-BFFA model

The prediction of the syn flood attack is implemented on the KDD cup dataset. Table 1 presents the basic information of the dataset. The learning model initializes the parameter using BBA, TDLHBA, and BFFA optimization algorithms. In this experiment, we used 30% of test data for calculating the accuracy. Our neural network model has two fully connected hidden layers and one output layer with a single neuron. The hidden layer width is set to 30 based on the initialization value. The fully connected hidden layers

Table 2
Dense layer and parameters.

Parameters	Value
Units	30
Activation	relu
Initializer	uniform
Dimensions	25

Table 3
Optimal parameters for different algorithms.

Parameter	BBA	TD HLBBA	BFFA
Batch Size	10	10	10
Number of Epoch	20	30	20
Learning Rate	0.0017	0.0017	0.00174
Number of neurons	20	40	30

are using ReLU nonlinear activation function. The classifier (output layer) is defined as a sigmoid activation function to detect the attacks. The model is compiled with a batch size of 10 and the learning rate is 0.00174 for 20 epochs. Early stopping is applied to stop the training once the improved accuracy is reached.

Table 5 presents the performance evaluation results of all the optimization models. It has been observed that both the Syn network model and TDLHBA achieve good accuracy as compared to the BBA algorithm. It has interfered that our proposed model outperformed the test classifier. This model achieves 99.96% accuracy in detecting the attacks.

The following Fig. 4 shows the detection accuracy for the proposed model. It has been observed that both the training and testing accuracy are increased linearly. Because the model learns the feature well and considers important features for training and testing. The loss of the training and testing phase is shown in Fig. 5.

Table 5
Performance metrics of proposed model.

Model	Loss	Accuracy
Syn Network Model	0.6985	0.9891
TDLHBA	0.0020	0.9901
BBA	0.0016	0.9794
BFFA	0.0011	**0.9996**

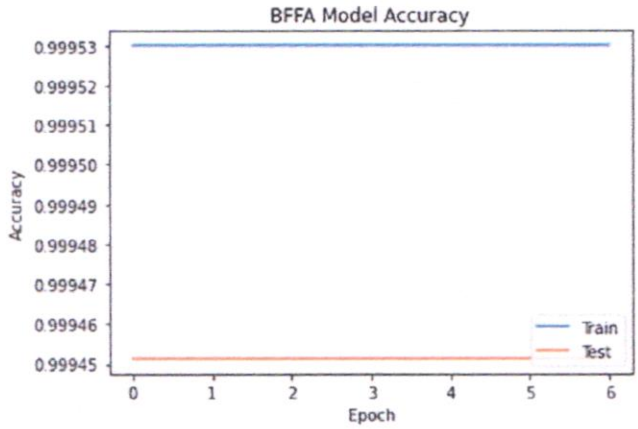

Fig 4. Accuracy of the BFFA Model.

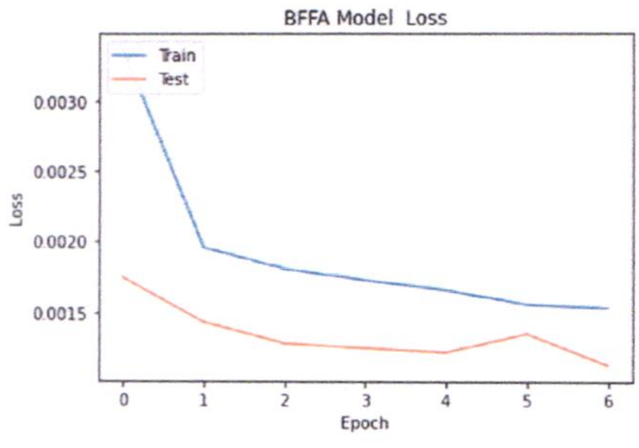

Fig 5. Loss of the BFFA Model.

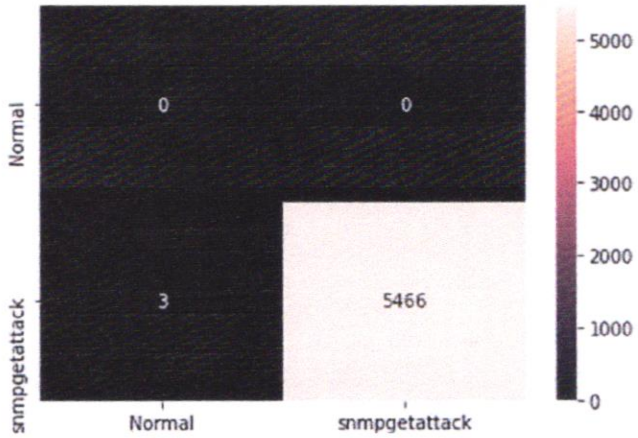

Fig 6. Confusion matrix for BFFA model.

Table 6
Proposed model compared to the existing model.

Model	Loss	Accuracy
BRNN	0.0901	0.9794
BFFA	**0.0011**	**0.9996**

5. Evaluation metrics

The proposed model is evaluated using a confusion matrix. It is a n*n matrix where n is the number of the actual classes. This matrix compares the actual class to the predicted class by using the deep learning model. Each column represents the actual value of the class and rows are related to the predicted class of the data. The validation size of the data is 5469. Fig. 6. Show the confusion matrix for the BFFA model. This model correctly predicts the attacks on 5466 data and only three data are wrongly predicted. This metric proves that the proposed model is well designed to predict attacks.

6. Comparison of the proposed model

The authors of [20–22] proposed a deep learning model to detect the DDoS attack using a recurrent neural network classifier. This model has achieved an error rate of 2.1% for detecting the attacks. This classifier was used to trace the network attack activities and the sequences of the network traffic. Our proposed BFFA model improves 3.5% detection accuracy as compared to the existing classifier model. The revised feature extraction technique is used to extract important features to avoid over fitting. See (Table 6).

7. Conclusion

In DDoS attack detection, the deep learning-based classifier produces better accuracy and less prediction time as compared to other deep learning algorithms. This algorithm can able to handle different kinds of attacks in the network system. In this research work, the authors presented a novel BFFA algorithm by utilizing the swarm intelligence approach for optimal parameter findings. The neural network parameters are tuned by using the optimal metric values. Conventional deep learning models are designed using hand-picked parameter values. The experimental results of the BFFA model show that the detection accuracy is high as compared to the existing models. The comparison of the existing approach with the proposed algorithm is described in terms of the accuracy with the same dataset. In the future, the authors have a focus on unidentified attacks for preventing cyber security issues in the field of IT applications and the banking sector.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] C.C. Center, Cert advisory ca-1996-21 TCP SYN flooding and IP spoofing attacks, 1996.

[2] R. Wang, Z. Jia, L. Ju, An entropy-based distributed DDOS detection mechanism in software-defined networking in Trust Com/Big Data SE/ISPA (1). IEEE, 2015, pp. 310–317.

[3] A. Sangodoyin, B. Modu, I. Awan, J. Pagna Disso, An approach to detecting distributed denial of service attacks in software defined networks, IEEE 6th Int. Conference on Future Internet of Things and Cloud, Barcelona, Spain, 6-8 Aug. 2018.

[4] L. Barki, A. Shidling, N. Meti, D.G. Narayan, M.M. Mulla, Detection of distributed denial of service attacks in software defined networks, 2016 Intl. Conference on Advances in Computing, Communications and Informatics (ICACCI), Sept. 21-24,2016.

[5] S. Hameed, H.A. Khan, SDN Based collaborative scheme for mitigation of DDoS attacks, Future Internet 10 (2018) 23, https://doi.org/10.3390/fi10030023, 27 Feb 2018.

[6] M. Bogdanoski, T. Shuminoski, A. Risteski, Analysis of the SYN flood DoS attack, I. J. Computer Network and Information Security, 2013, 8, 1-11 Published Online June 2013 in MECS (http://www.mecs-press.org/) DOI: 10.5815/ijcnis.2013.08.01.

[7] O. Kupreev, E. Badovskaya, A. Gutnikov, DDoS attacks in Q4 2018, on February 7, 2019, Kaspersky Lab report.

[8] A. Sangodoyin, B. Modu, I. Awan, J.P. Disso, An approach to detecting distributed denial of service attacks in software defined networks, IEEE 6th International Conference on Future Internet of Things and Cloud, Barcelona, Spain, 6-8 Aug. 2018.

[9] R. Sridhar, S. Baskar, V.S. Shaisundaram, K. Karunakaran, M. Ruban, S.J.I. Raja, Design and development of material behavior of line follower automated vehicle, Mater. Today: Proceedings 37 (2021) 2193–2195.

[10] S.M. Mousavi, M. St-Hilaire, Early detection of DDoS attacks against SDN controllers, 2015Int. Conf. Comput. Netw. Commun. ICNC2015 (2015) 7781.

[11] R. Wang, Z. Jia, L. Ju, An entropy-based distributed DDoS detection mechanism in software-defined networking, Proc. - 14th IEEE Int. Conf. Trust. Secur. Priv. Comput.Commun. Trust.2015, vol. 1, pp. 310317, 2015.

[12] J. Ashraf, S. Latif, Handling intrusion and DDoS attacks in Software Defined Networks using machine learning techniques, 2014 Natl. Softw. Eng. Conf.,pp. 5560, 2014.

[13] N.K. Chandramohan, M. Shanmugam, S. Sathiyamurthy, S.T. Prabakaran, S. Saravanakumar, V.S. Shaisundaram, Comparison of chassis frame design of Go-Kart vehicle powered by internal combustion engine and electric motor, Mater. Today: Proceedings 37 (2021) 2058–2062.

[14] R.T. Kokila, S. Thamarai Selvi, K. Govindarajan, DDoS detection and analysis in SDN-based environment using support vector machine classifier, in: in 2014 Sixth International Con-ference on Advanced Computing (ICoAC), 2014, p. 205210.

[15] N. Meti, D.G. Narayan, V.P. Baligar, Detection of distributed denial of service attacks using machine learning algorithms in software defined networks, in 2017 InternationalConference on Advances in Computing, Communications and Informatics (ICACCI),2017, pp. 13661371.

[16] D. Hu, P. Hong, Y. Chen, FADM: DDoS flooding attack detection and mitigation system in software-defined networking GLOBECOM 2017–2017IEEE Global Communications Conference 2017 17.

[17] S.J. Stolfo, W. Fan, W. Lee, A. Prodromidis, P.K. Chan, Cost-based modeling for fraud and intrusion detection: results from the jam project, vol. 02, p. 1130, 2000.

[18] https://github.com/nsnakhil/AI_Cybersecurity_finalproject/tree/master/dataset.

[19] A. Shiravi, H. Shiravi, M. Tavallaee, A.A. Ghorbani, Toward developing a systematic approach to generate benchmark datasets for intrusion detection, Computers Security 31 (3) (2012) 357–374.

[20] G. Revathy, P.S. Kumar, V. Rajendran, Development of IDS using mining and machine learning techniques to estimate DoS malware, Int. J. Comput. Sci. Eng. 24 (3) (2021) 259–275.

[21] X. Yu, D. Han, Z. Du, Q. Tian, G. Yin, Design of DDoS attack detection system based on intelligent bee colony algorithm, Int. J. Comput. Sci. Eng. 19 (2) (2019) 223, https://doi.org/10.1504/IJCSE.2019.100243.

[22] S. Saravanakumar, N.K. Chandramohan, S.T. Prabakaran, M. Muniyappan, M. Shanmugam, V.S. Shaisundaram, The static structural analysis of torque converter material for better performance by changing the stator angle, Mater. Today: Proceedings 37 (2021) 1963–1972.

[23] X. Yuan, C. Li, X. Li, Deep defense: identifying DDoS attack via deep learning, IEEE Int. Conf. Smart Comput. (SMARTCOMP) 2017 (2017) 1–8, https://doi.org/10.1109/SMARTCOMP.2017.7946998.

[24] V. Dr Devi, Dr. D. Ravikumar, Dr. M. Meena, Dr. E.N. Ganesh, Dr. V. Janakiraman, Distributed denial of service detection and mitigation solutions in software defined radio networks, Journal of Xidian University, 14, 6, 2020 1536-1541.

[25] Dr. E.N. Ganesh, Dr.V. Rajendran, Dr. D. Ravikumar, P. Sai Kumar, G. Revathy ,P. Harivardhan, Remote sensing analysis framework for maritime surveillance application, International Journal of Oceans and Oceanography, Vol 15, Number 1, pp 11-17, ISSN 0973-2667, June 2021.

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Side scan sonar image augmentation for sediment classification using deep learning based transfer learning approach

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ABSTRACT

Object detection in underwater acoustics especially sea floor object has been overwhelming mission chiefly owing to strident environment of sonar images as well as because of visibly existing sonar images. Side Scan Sonar is the primary sensor for Autonomous Underwater Vehicles to perform survey on sea water. Hence, we are using this SSS images for categorizing several objects like sand, mud, clay, graves, ridges and sediments in underwater sea through any size subsequent to training. We applied two-layer CNN architecture to train the model as well as we utilized three pre-trained network models such as VGG-19, ResNet50 and EfficientNet model for evaluating the performance of the model based on training and validation accuracy measures. Moreover, we utilized deep learning based transfer learning approach in which the parameters are tuned for classifying the images into sediments, clay, mud, stones etc. Our experimental outcomes shows that pre-trained EfficientNet model generates better accuracy of 100% after fine tuning the parameter in object recognition along with classification using SSS images.

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1. Introduction

For underwater investigation and imagery, SSS expertise has been utilized for over three decagons. Archaeology, security and defence, seabed categorization, and ecological investigation are some of the applications for side-scan sonar. Data collecting has become more automated in modern years because to the introduction of autonomous underwater equipment. Convolutional Neural Networks have been extensively utilized in several researchers with categorization and object detection in underwater acoustics in current years. Huo et al. [9] anticipated semi-synthetic data production approach for categorizing sonar images into several objects like mud, clay, mine, rock, etc. Also, they applied pre-trained model namely VGG-19 also fine tuning the data which attains 97.76% accuracy in object classification in underwater. The architecture proposed by [9] is depicted in Fig. 1.

1.1. Objectives

The main objective of the proposed work is mentioned as follows:

- To gather Side Scan Sonar dataset taken from underwater acoustics seafloor.
- To perform augmentation technique for construct the categorization models which helps to categorize sonar datas into rock, mud, clay, sand and some other related minerals.
- To introduce the pre- trained the neural network model such as VGG-19, ResNet50 and also EfficientNet model for evaluating training and validation accuracy
- To detect the metal mine objects such as rock, mud, clay and sand from seafloor images and classification of the image using transfer learning.

1.2. Motivation

The major challenge is inadequacy of sufficient Side Scan Sonar data sets required for training the proposed models. Data augmentation is used to build the classification models.

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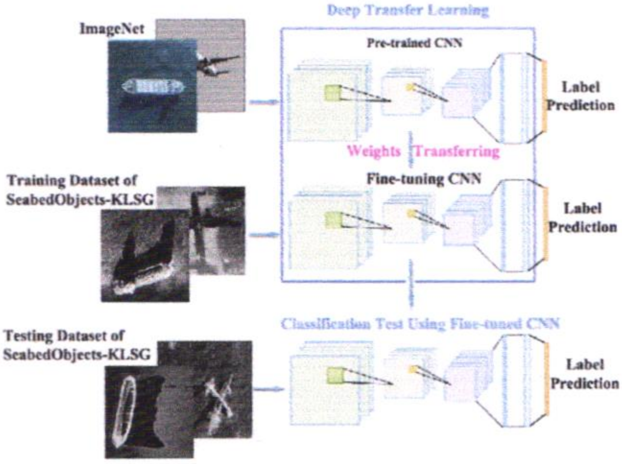

Fig. 1. Architecture introduced for object classification.

2. Related work

During 1998, Bull et al. [10] estimated reflection co-efficient from Chirp data and they applied whether it is applicable to archeological studies. Yan Song et al [27] applied deep learning based CNN especially Markov Random Fields for segmenting the SSS images into several objects like sand, clay, mud etc. Qin et al. [18] proposed deep learning based Convolutional Neural Networks as well as CIFAR-10 based grayscale for pre-train the model to accomplish features relocation including enhancement in performance of model. After fine tuning, ResNet approach reached an error rate of 3.46%. Anuja Pharate et al. [2] applied support vector machine and principle component analysis were utilized to categorize SSS images into mud, rock, mine, clay. Object recognition as well as classification in underwater acoustics especially sea floor using Gaussian mixture approach by kannan et al. [12] achieves 99% accuracy, one-dimensional based Convolutional Neural Network model with Jun Yan et al. [11,28], multidimensional based deep learning approach by Tsai et al. [3] Apriori modeling applied by Naveen kumar et al. [17], deep learning based CNN used by Fenglei Han [6], Sejin Lee et al. [22], Einsidler et al. [4,14], depends on physics modeling by Christina Fredrick et al. [7], edge based segmentation approach tried by Priya dharshini et al. [20], active learning method Dura et al. [5], machine learning technique Zhang et al. [33], especially decision tree for SSS matching Sylvie Danielet al. [26] Fuzzy means clustering technique Chang. R et al. [19], transfer learning based YOLOv3 approach by Yulin et al. [31] from side scan sonar images. Feature extraction has done from side scan sonar image for underwater acoustics Nayak et al. [16,21],also unsupervised removal of features from SSS images by Morissette et al. [8], extracting relevant parameters based on deep learning for object classification in underwater completed by Zhu et al. [32]. Image segmentation in underwater acoustics using efficient Convolution network by Meihan Wu et al. [15], based on extreme learning machine developed by Yan Song et al. [24,29]. In addition, classifying objects in underwater acoustics from SSS images by [Jason Rhinelander]. Many researchers namely Yujie Chen et al. [30], Lubis et al. [13] reviewed several article regarding underwater object detection from SSS images or dataset using neural network method Shraddha et al. [23], watershed segmentation [1] based on markers to specify the regions [33–38].

3. SSS dataset and methods

3.1. Underwater seafloor SSS image dataset

Authors build a real and synthesis dataset from seafloor sidescan sonar images. The dataset used in this project is built by using data augmentation techniques such as rotation, translation, scaling, and cropping can be employed to increase the size of the available dataset [25].

The details about training and testing samples portion for each objects such as rock, mud, clay, sand, sandwaves and sandridges from underwater SSS images are listed in Table 1.Here, we have taken SS sonar data from sea floor acoustics like rock, mud, clay, sand, waves and ridges with 41 training samples and 10 testing samples which undergoes classification of sediments. Hence, totally 51 samples are utilized for each underwater acoustics objects.

3.2. Sample SSS data

Fig. 2 depicts the objects available in underwater acoustics using sonar images.

3.3. Modules in proposed model

In proposed work, we have five modules for sediment classification using SSS images. Each module for sediment based classification is described below.

3.3.1. Module 1: Gathering side scan sonar (SSS) images

Here, SSS images have been gathered from specified link or some other resources related with underwater sea floor for finding objects and also classification.

3.3.2. Module 2: Data augmentation

Data augmentation technique is utilized for enlarging the sonar dataset with the aim of enhancing the performance of model to simplify. It consists of shifting, rotation, translation, scaling and cropping images to transfer the original image pixels into another format named as transformed image (SSS). This can be done using deep learning based Keras library through *ImageDataGenerator* class.

To identify the objects like mines, rocks, mud, clay and other minerals, we illustrate the outline for sonar image as shown like Fig. 3. While we enlarge the sonar image, we need to place outline box furthermore designate modernized consequently. For making boundary for sonar image, ImgAug (ImageAugmentation) is used. While we perform operations such as rotation, shear, translation and cropping the sonar image, fixing the border line in the specific region of rocks, mud, or clay is also updated consequently.

i. Rotation

Rotation technique specifically used to rotate the underwater sonar image by a precise level. Here in figure we can see how the

Table 1
SSS image data description.

Data	Training	Testing	Total
Rock	41	10	51
Mud	41	10	51
Clay	41	10	51
Sand	41	10	51
Sandwaves	41	10	51
Sandridges	41	10	51

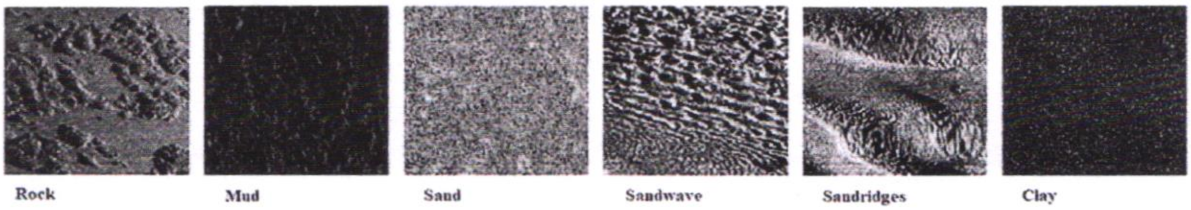

Fig. 2. Sample SSS data.

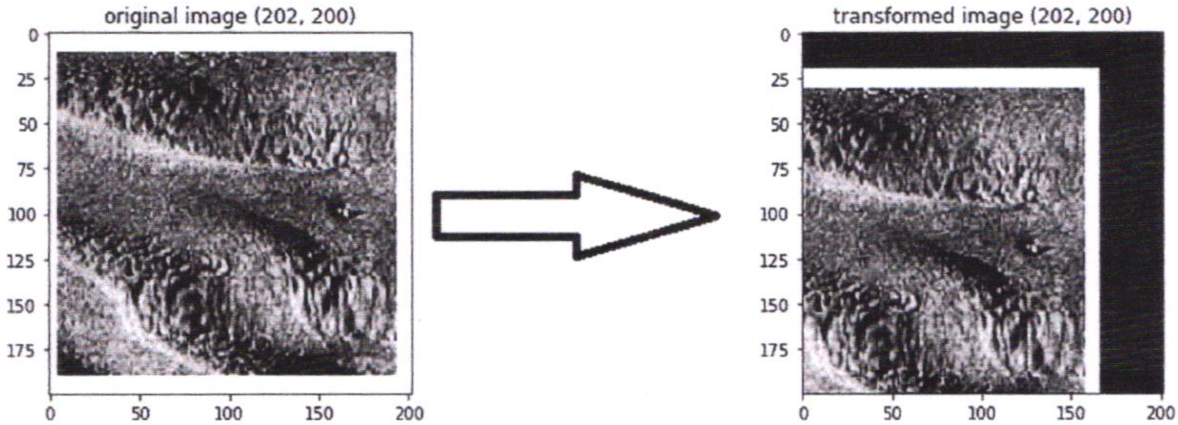

Fig. 3. Rotation approach applied on SSS image.

original sonar image with pixels (202, 200) is malformed into transformed image with similar pixels dimensions of (202, 200). We are revolving the sonar image by 50 to 40 degrees for modifying image quality to enhance the image performance.

Here is the python code for rotation technique that makes the underwater acoustic sonar image alternate the position to a specific degree.

Loader_Transform = Transforms. RandomRotation (10)

Imshow ('sandridges.png', LoaderTransform)

ii. Translation

Translation defines that SSS image is transformed into either along horizontally means x-axis or along vertically which represents y-axis shown in Fig. 4. Here is the python code for translation technique that makes the underwater acoustic sonar image to transform into another specified image depends on axes (both x-axis and y-axis).

Loader_Transform = Transforms. RandomAffine (0, translate = (0.4, 0.5))

Imshow ('sandridges.jpg', Loader_Transform)

iii. Scaling

Scaling can be used for scale the sonar image into either zoom in or zoom out. Now, we are scaling the sonar image into 140% to 140% of the sonar image which represents height and width. By using both x-axis and y-axis, we are scaling the image separately which is depicted in Fig. 5. This transformation modifies the objects those are available in underwater acoustics. By using this operation, the height and width of the sonar image may get reduced or enlarged. We attained this operation by proliferate

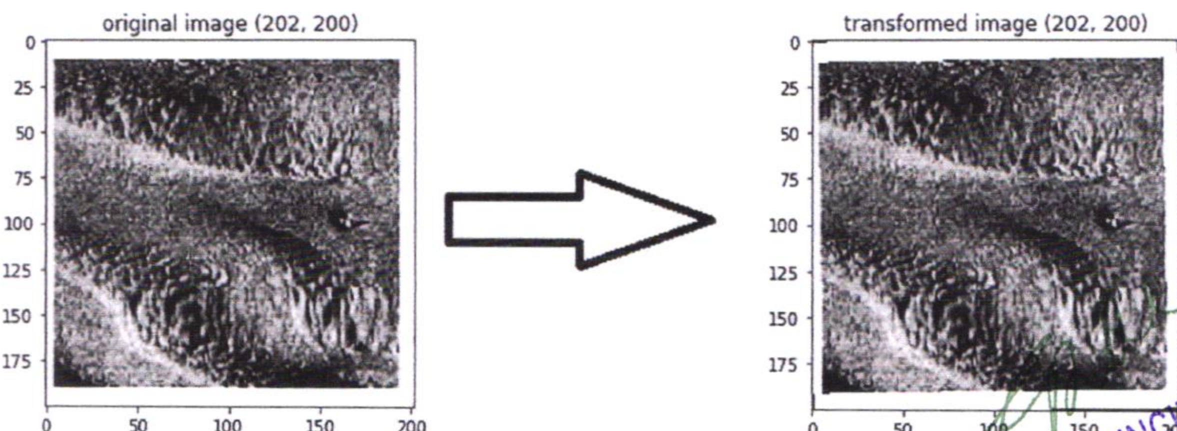

Fig. 4. Side scan sonar image translation.

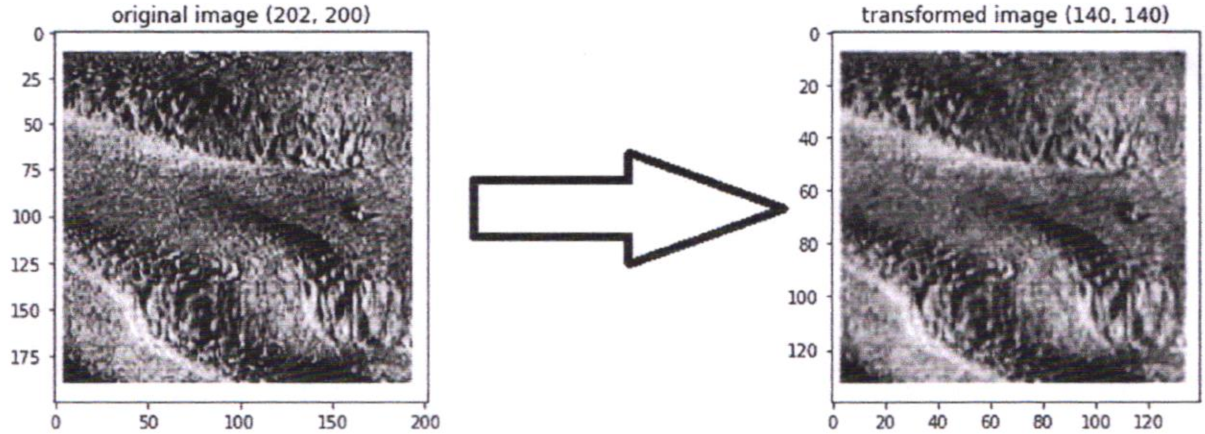

Fig. 5. SSS image scaling approach.

every vertex (X, Y) with specified scaling factor represented as (S_X, S_Y) to generate the translated co-ordinates as ($\overline{X}$, $\overline{Y}$). Here is the python code for scaling technique that makes the underwater acoustic sonar image into either compressing or expand the size of the image.

```
Loader_Transfrom = Transforms.Resize ((140, 140))
Imshow ('sanridges.png', Loader_Transform)
```

iv. Cropping

In this operation, the original sonar image is cropped by nearly 140%. Here the objects seen in sonar image emerge in dissimilar location with dissimilar ratio. It eliminates both rows as well as columns at the surface of sonar image which is shown in Fig. 6.

By using the following python programming code, cropping operation has done through reducing the columns and also rows in sonar image outside.

```
Loader_Transform = Transfroms. CenterCrop (140)
Imshow ('sandridges.png', Loader_Transform)
```

3.3.3. Module 3: Training and testing

Training the data: Training the side scan sonar images is necessary important especially categorizing sediments from seafloor which helps to fit the network model. Hence we are applying deep learning based neural network to train the model based on SSS dataset.

Validating the data: Validating SSS image dataset indicates that these images are utilized to afford balanced estimation of any model which suits on training sonar images when the model is tuned (hyper parameter tuning). The assessment turned into additionally imbalance as ability on validation sonar images that are integrated into novel modern design.

Testing the data: Testing dataset afford balanced assessment of ultimate model suits on training dataset. This part is considered as standard segment in evaluating the model exactly. Testing the images is used only once a model is entirely trained with both training and validation of sonar images. Wholly, testing the images is utilized to estimate challenging network approaches. The splitting sonar images into specified ratio is shown in Fig. 7.

3.3.4. Module 4: Pre-trained models

i. VGG-19 model

The framework of VGG-19 model comprises of Convolutional layers (16) with 5 grouping, connected layers (3). Hence, this model has 19 layers along with features entirely. Since VGG Network model is appropriate for transfer learning, VGG-19 representation is utilized in this proposed model which is depicted in Fig. 8.

ii. ResNet50 model

We trained the neural network model up to 30 epochs for identifying the sediments in underwater sea and undergoes classifica-

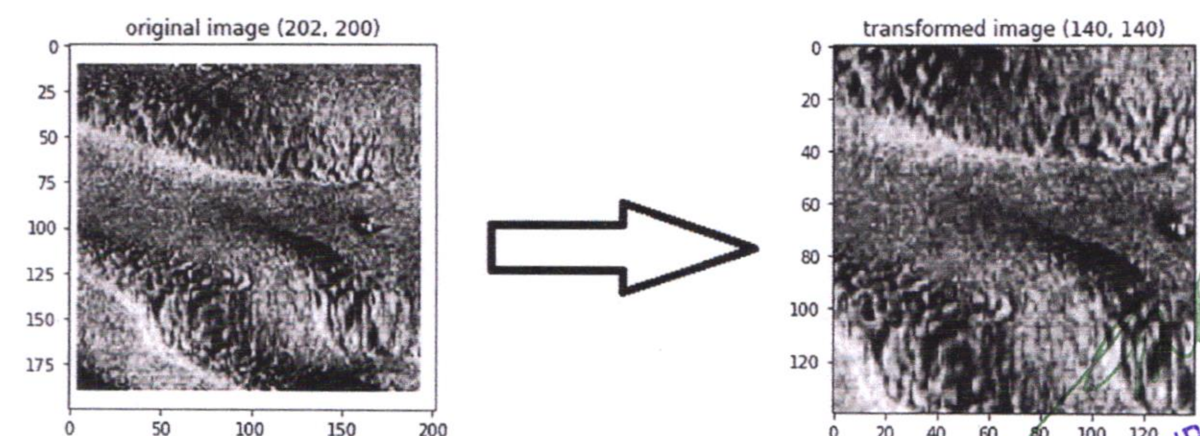

Fig. 6. Image cropping using SSS underwater data.

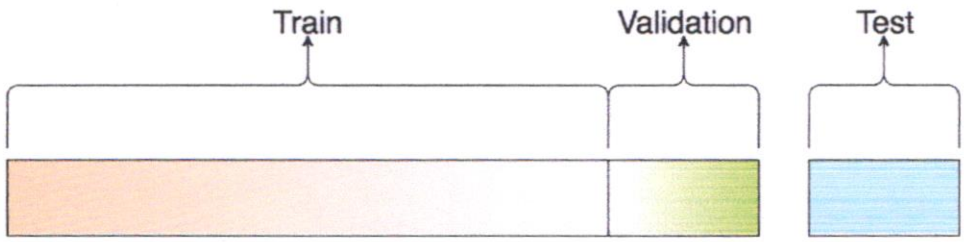

Fig. 7. Splitting sonar data in this ratio.

tion by estimating accuracy, loss, validation accuracy and validation loss for ResNet50 model.

iii. EfficientNet model

The baseline network has a big role in reproduction scaling's success. To enhance performance even more, we created a novel baseline network by using the AutoML MNAS structure to do a neural network framework search that optimizes mutually accuracy as well as efficiency. Our result shows that EfficientNet model generates greater accuracy as 100% with least amount of loss.

3.3.5. Module 5: Proposed fine tuned model

This proposed fine tuning of parameters generates more accuracy to enhance the overall model performance. Also, efficiency of model will be improved. Fig. 9 portrays that comparison has done among fine tuning of network model is with transfer learning and without transfer learning.

4. Proposed CNN architecture and transfer learning approach

Here we are introducing two CNN based architecture for identifying minerals like objects such as mines, rocks, sand, clay, mud, gravels etc in underwater sea acoustics using side scan sonar images. They are two-layer neural network based model as well as deep learning based transfer learning algorithm.

4.1. Two-layer neural network model

This model comprises of original sonar data along with augmented data with Convolutional Neural Network layer with ten epochs. The CNN based two-layer NN architecture is shown in Fig. 10.

Convolutional Layer: The Convolutional layer has a number of strains (filters) whose features must be academic. The strains altitude, load are less than that of the input volume. Every strain is convolved with the input volume to produce a neuron-based activation map.

Pooling layer: The parameter map magnitudes are reduced by using pooling layers. As a result, the number of attributes to be trained and the amount of processing in the network are both reduced. The features contained in a region of parameter map produced by a convolution layer are summed up by the pooling layer.

Flatten layer: Flatten is a function that takes a pooled feature map and turns it into a single column that can be supplied to a fully linked layer. Dense gives the neural network a completely linked layer.

Dense layer: A closely linked layer provides learning features from all the amalgamation of the features of the previous layer, but a Convolutional layer relies on reliable features with a small repetitive field. Here, we are using the size of dense layer as ten and the number of epochs used for training the data samples as 20.

FC layer (Classifier)- Now our designed CNN based Neural Network model using SI-BBA is suitable for classifying the data samples into phishing attack websites (malignant) and normal (legitimate).

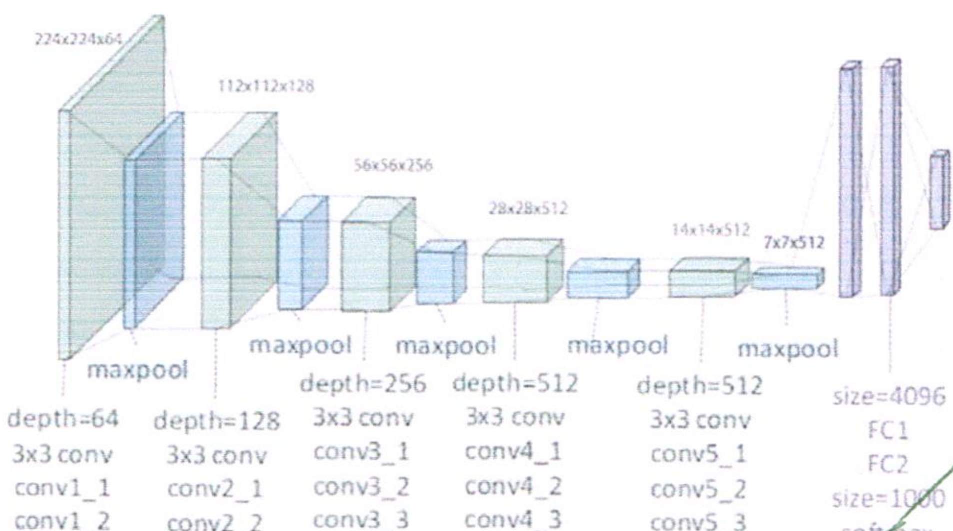

Fig. 8. VGG-19 framework for object classification through layers.

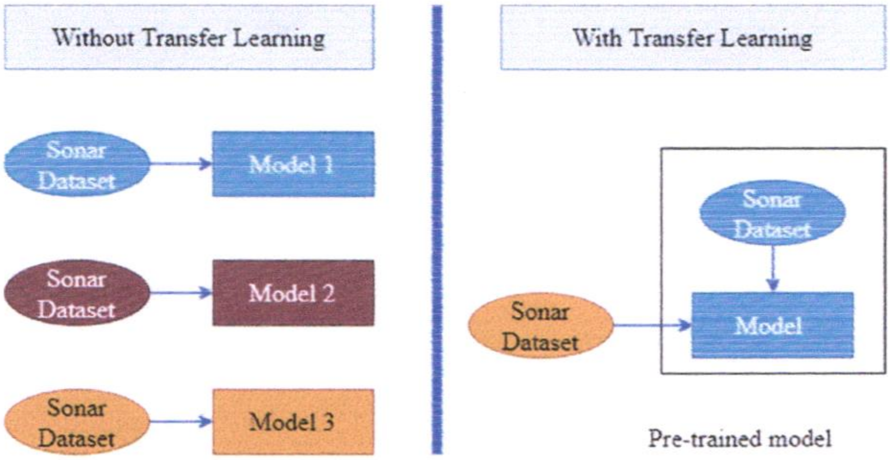

Fig. 9. Comparison among using transfer learning and without TL.

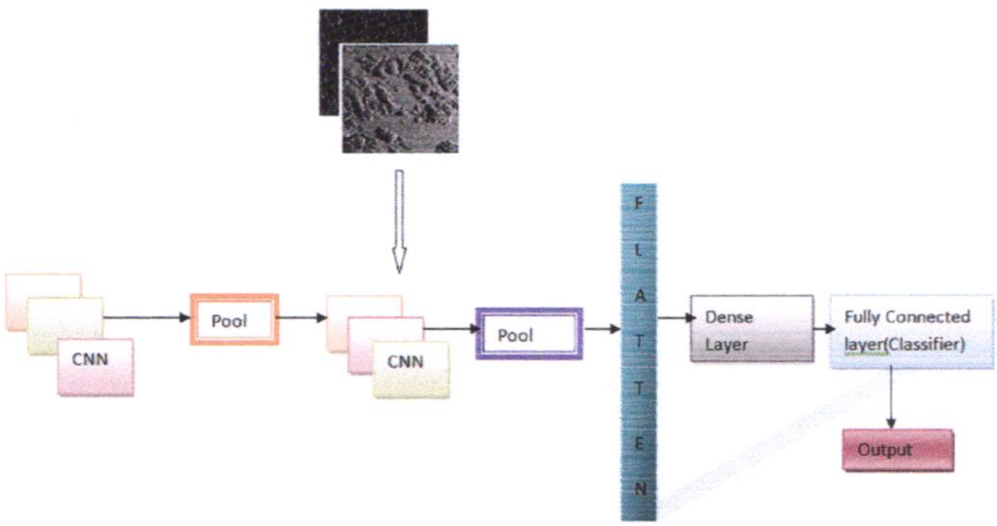

Fig. 10. Two-layer Neural Network model.

Output layer: This layer generates the precise output for the given input. The input images are classified into normal and abnormal (Cardiac Amyloidosis) shown in the output section.

4.2. Deep learning based transfer learning approach

The architecture of deep learning based transfer learning scheme is described in Fig. 11 which explains that initially original sonar data have taken, then those datas are augmented, followed by pre-trained the models such as VGG-19, ResNet50, EfficientNet, then introducing fine tuning of classifier to categorize the SSS data

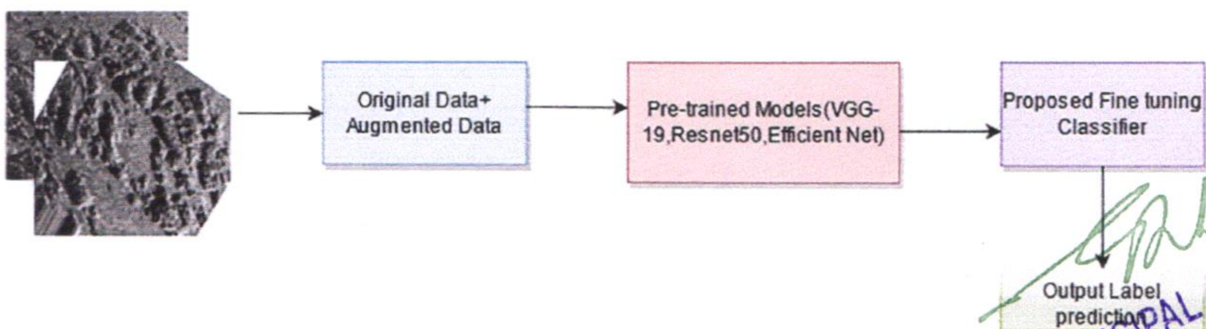

Fig. 11. Deep learning based transfer learning approach.

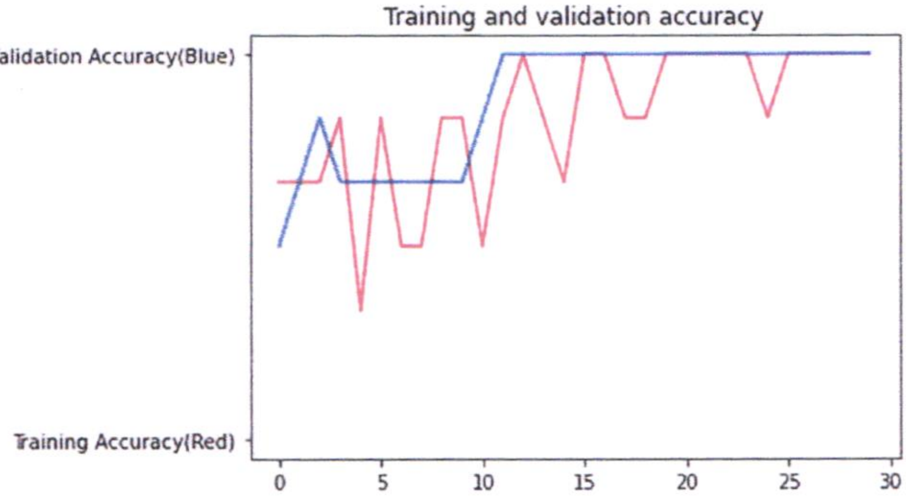

Fig. 12. Training accuracy Vs Validation accuracy.

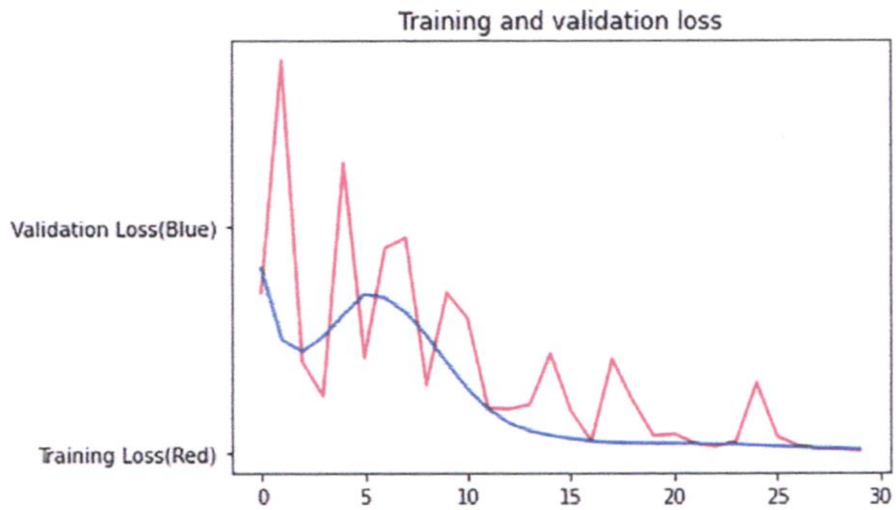

Fig. 13. Training loss Vs Validation loss.

into mine, rock, sediment, sand, mud, clay etc. Finally the output will be predicted via validation phase.

Transfer Learning approach is one of the deep learning based approach wherever we know how to receive the pre-trained network based approach also utilize it as initial stage to find out advanced event. It is usually considerably faster and easier to fine-tune a network with transfer learning than it is to train a network from start with randomly initialized weights. With a smaller, limited number of training photos, we are able to transfer quickly that are previously learned characteristics to a new task and identify new targets. Nowadays transfer learning based deep learning approaches are applied in the domain of medicinal applications such as disease diagnosis, disease classification (normal/abnormal) from images. Hence in this paper we are applying transfer learning technique for detecting underwater objects as well as classifying the objects into sediments, clay, mud, graves, sand, soil, rock etc.

5. Evaluation of metrics

Based on evaluation on metrics such as training accuracy, validation accuracy, training loss and validation loss, we undergo classification of objects in underwater sea using SSS images. The evaluated metric are described below.

Training accuracy: Accuracy is defined as metric so as to usually express how the deep learning approach executes diagonally every section. This may helpful while every potions having identical significance. Accuracy is estimated as the ratio among the number of correct predictions to the total number of predictions. Based

Table 2
Metrics evaluation comparison has done before tuning as well as after fine tuning the parameters.

	Training Accuracy (%)	Validation Accuracy (%)	Training Loss	Validation Loss
Before tuning	88.89	97.62	0.457	0.118
After fine-tuning	97.22	98.41	0.486	0.016

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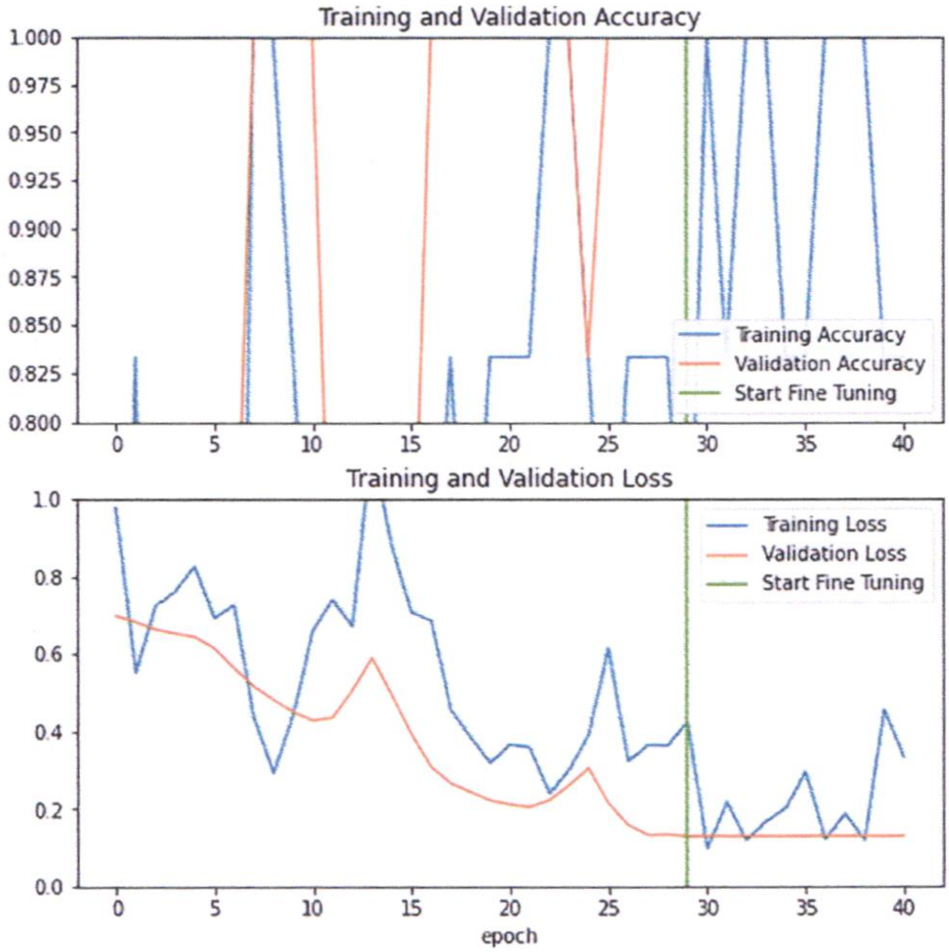

Fig. 14. Training accuracy, loss Vs validation accuracy, loss using VGG-19.

Table 3
Comparison among before tuning and after fine tuning for accuracy and loss metrics.

	Training Accuracy (%)	Validation Accuracy (%)	Training Loss	Validation Loss
Before tuning	66.66	100	0.423	0.128
After fine-tuning	83.33	100	0.342	0.180

on True positive, true negative, false positive, and False negative metrics we are evaluating the accuracy to find the performance of the model.

Validation accuracy: Testing accuracy is otherwise named as validation accuracy. After training the sediment data, the accuracy metric is calculated for evaluating the performance of the model based on this validation.

Training loss: Training loss is the inaccuracy on the working out set of sonar data or images

Validation loss: The validation loss is calculated following the same epoch's learning phase.

Epoch: One epoch is defined as when the complete dataset visited both front and rear through neural network only once. The amount of epoch is a hyper parameter that defines how many times that the learning algorithm can be done through the complete training dataset.

6. Experimental outcomes

The explanation behind fine tuned of parameters is that relocating VGG-19 deep learning based approach may execute fine through pre-training VGG-19 model on EfficientNet model which

Table 4
Comparison among before tuning and after fine tuning for accuracy and loss metrics.

	Training Accuracy (%)	Validation Accuracy (%)	Training Loss	Validation Loss
Before tuning	83.33	100	0.557	0.429
After fine-tuning	100	83.33	4.535	0.430

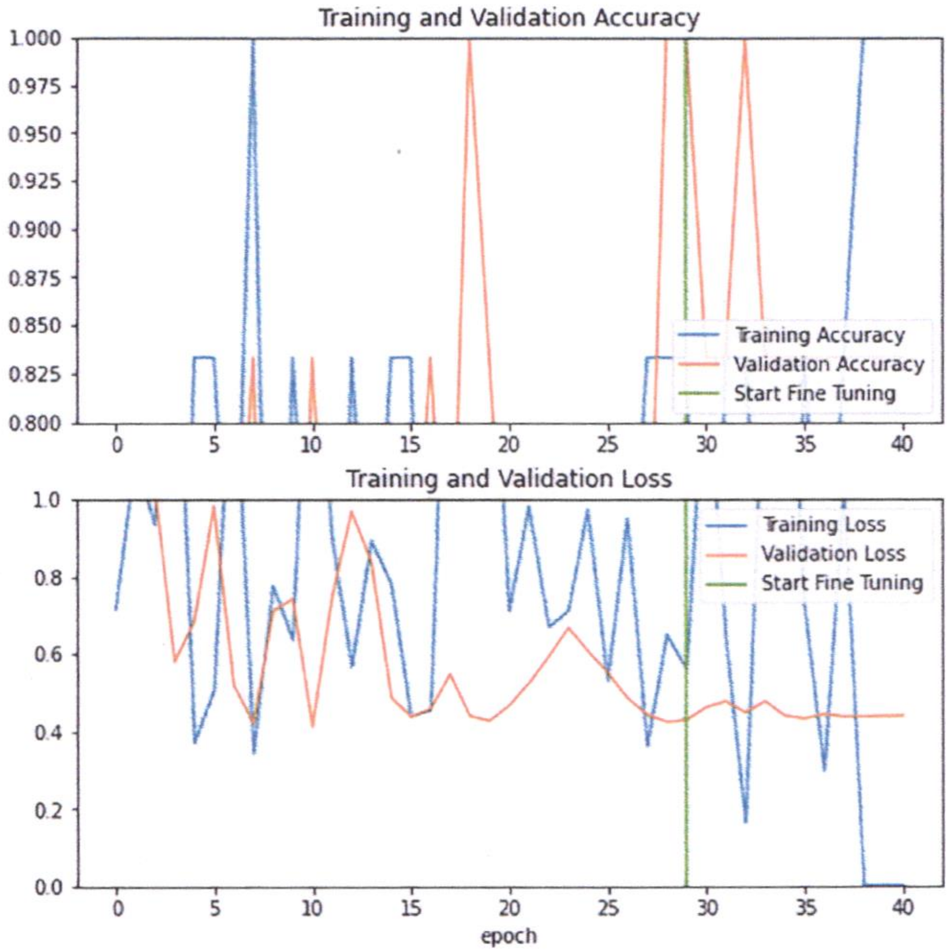

Fig. 15. Training accuracy, loss Vs validation accuracy, loss using ResNet50 model.

Table 5
Comparison among before tuning and after fine tuning for accuracy and loss metrics using EfficientNet model.

	Training Accuracy (%)	Validation Accuracy	Training Loss	Validation Loss
EfficientNet	100	100	0.081	0.006

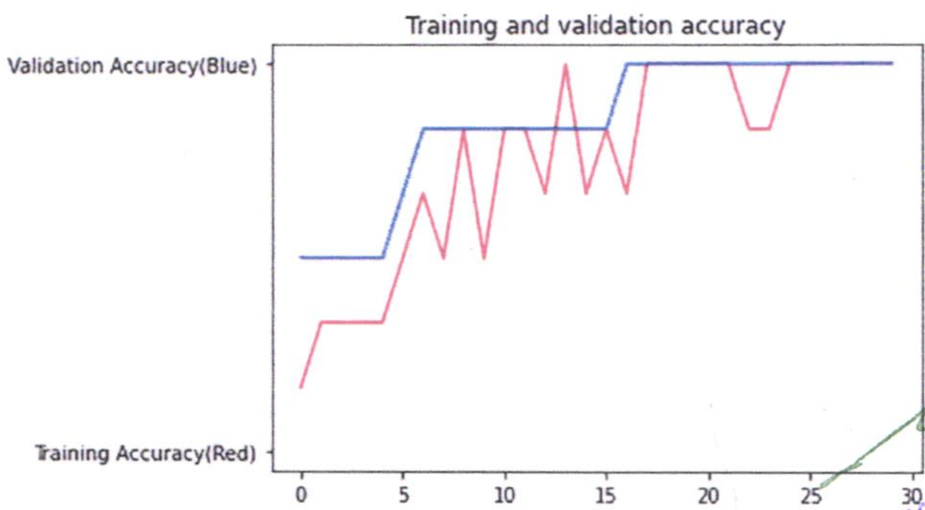

Fig. 16. Training accuracy Vs validation accuracy using EfficientNet model.

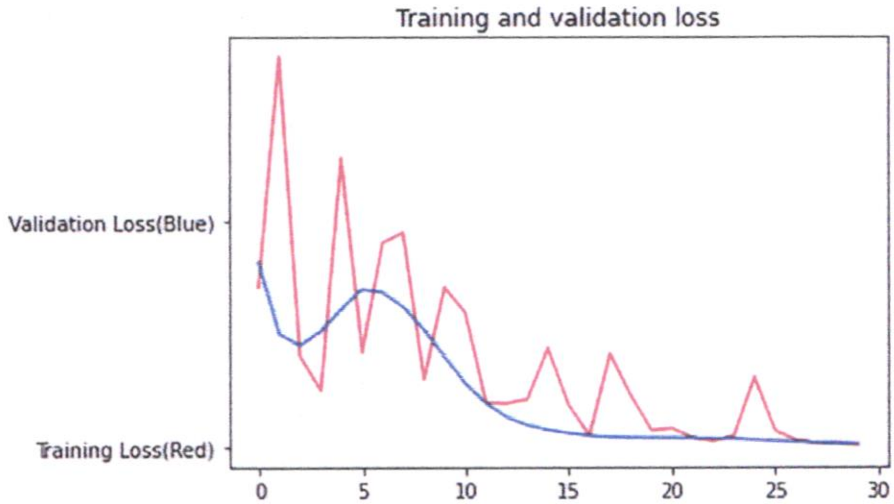

Fig. 17. Training loss Vs validation loss using EfficientNet model.

comprises of plentiful objects, the trained VGG-19 already learnt adequate parameters for detecting several types of underwater acoustics objects. By means of fine tuning the VGG-19 scheme, the object weights are rapidly attuned that is appropriate for SSS images. In this work why we are not using shallow CNN since it is not possibly being utilized to categorize intricate outline that needs little bit deeper model. Hence we are using deep learning based network model with 30 epochs. The accuracy with validation as well as training accuracyis estimated using two-layer CNN model which is depicted in Fig. 12, hence training loss and validation loss graph is shown in Fig. 13 and Table 3 (Table 2).

6.1. Classification using simple 2-layer CNN model

6.2. Pre-trained VGG-19 model

For evaluation, training improvement of 30 epochs of not-deep model for pre-trained VGG-19 model is depicted in figure. We observe that during training phase a non-deep model from scrape fight back for optimal convergence with ten epochs. By tuning the parameters the relocating VGG-19 approach is ability to attain greater performance. Even though pre-trained the deep learning based neural network approach such as VGG-19, ResNet50 on EfficientNet scheme. Subsequently fine tuned those VGG-19, ResNet50 approaches on actual sonar training dataset know how to attain better outcomes when compare to other approaches. If any imbalance happened, then it leads to wrong classification. The pre-trained models training accuracy and validation accuracy is depicted in Fig. 14 and training loss vs validation loss is shown in Fig. 14 as well as Table 3.

6.3. ResNet50

For evaluation, training improvement of 30 epochs of not-deep model for pre-trained ResNet50 model is depicted in Table 4 and Fig. 15. The validation accuracy and training accuracy is estimated by tuning the hyper parameters of side scan sonar images to extract the features also attaining greater performance in object recognition as well as classification.

6.4. EfficientNet

The EfficientNet model is a fine-tuned classifier which is being utilized for sediment classification using side scan sonar images taken from underwater acoustics sea floor. Both training and validation accuracy along with loss are depicted in Table 5, Figs. 16 and 17. Among other pre-trained models, our fine tuned model generates better results based on accuracy measures of 100% in sediment classification. Training accuracy is identified easily by the representation of red colour, validation accuracy represented by red colour.

7. Conclusions

The main target of this mission is to use side scan sonar images from a sub bottom profiler system to identify and segment sedimentary objects such as mines, rocks, clay, and mud that are positioned a few meters beneath the seabed. This will help with many underwater domain applications, especially metal mine detection. Also, we established that some deep learning based network model such as VGG-19, ResNet50 model were pre-trained and then fine tuning on CNN based EfficientNet model generates suitable outcomes based on accuracy measures as 100% in underwater object detection along with classification of objects into mines, rocks, clay, mud, graves, ridges and sediments.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] Amanpreetkaur, A. Verma, Ssiet, The marker based watershed segmentation a review, Int. J. Eng. Innov. Technol. (IJEIT) (2013).
[2] A. Pharate, J. Rangole, Sediment classification using side scan SONAR, IAETSD J. Adv. Res. Appl. Sci. 4 (7) (2017) 380–384, ISSN No: 2394-8442.
[3] C.-M. Tsai, Y.-H. Lai, Y.-D. Sun, Y.-J. Chung, M. Shortis, Sensors (Basel) 21 (3) (2021) 884, https://doi.org/10.3390/s21030884. Published online 2021 Jan 28.
[4] D. Einsidler, M. Dhanak, P. Beaujean, A Deep Learning Approach to Target Recognition in Side-Scan Sonar Imagery, in: OCEANS 2018 MTS/IEEE Charleston, 2018, pp. 1–4. doi: 10.1109/OCEANS.2018.8604879.
[5] E. Dura, Y. Zhang, X. Liao, G.J. Dobeck, L. Carin, Active learning for detection of mine-like objects in side-scan sonar imagery, IEEE J. Ocean. Eng. 30 (2) (2005) 360–371.
[6] F. Han, J. Yao, H. Zhu, C. Wang, H. Zhu, C. Wang, Underwater image processing and object detection based on deep CNN method, Hindawi J. Sens. (2020).

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[7] C. Frederick, S. Villar, Z.-H. Michalopoulou, Seabed classification using physics-based modeling and machine learning, J. Acoust. Soc. Am. 148 (2) (2020) 859–872, https://doi.org/10.1121/10.0001728.

[8] G. Labbe-Morissette, S. Gautier, Unsupervised extraction of underwater regions of interest in side scan sonar imagery, J. Ocean Technol. 15 (1) (2020) 95–108.

[9] G. Huo, Z. Wu, J. Li, Underwater object classification in sidescan sonar images using deep transfer learning and semisynthetic training data, IEEE Access 8 (2020) 47407–47418.

[10] J.M. Bull, R. Quinn, J.K. Dix, Reflection co-efficient calculation form marine high resolution seismic reflection data and application to an Archaeological case study, Mar. Geophys. Res. (1998).

[11] J. Yan, J. Meng, J. Zhao, Real-time bottom tracking using side scan sonar data through one-dimensional convolutional neural networks, J. Remote Sens. (2020).

[12] S. Kannan, Intelligent object recognition in underwater images using evolutionary-based Gaussian mixture model and shape matching, SIViP 14 (2020) 877–885, https://doi.org/10.1007/s11760-019-01619-w.

[13] M.Z. Lubis, H. Kausarian, W. Anurogo, Review: seabed detection using application of image side scan sonar instrument (Acoustic Signal), J. Geosci. Eng. Environ. Technol. 2 (3) (2017).

[14] M. Rahnemoonfar, D. Dobbs, Semantic segmentation of underwater sonar imagery with deep learning, IEEE Xplore, IGARSS 2019, pp. 9455–9458.

[15] M. Wu, Q. Wang, E. Rigall, K. Li, W. Zhu, B. He, T. Yan, ECNet: efficient convolutional networks for side scan sonar image segmentation, J. Sens. (2019).

[16] N. Nayak, M. Nara, T. Gambin, Z. Wood, C.M. Clark, Machine learning techniques for AUV side scan sonar data feature extraction as applied to intelligent search for underwater archaeological sites, Field and Service Robotics, SPAR 16, 219–233.

[17] N. Kumar, Q. Feng Tan, S.S. Narayanan, Object classification in sidescan sonar images with sparse representation techniques, ICASSP, 2012.

[18] X. Qin, X. Luo, Z. Wu, J. Shang, Optimizing the sediment classification of small side-scan sonar images based on deep learning, IEEE Access 9 (2021) 29416–29428.

[19] R. Chang, Y. Wang, J. Hou, S. Qiu, R. Nian, B. He, A. Lendasse, Underwater object detection with efficient shadow-removal for side scan sonar images, in: OCEANS 2016 - Shanghai, April 2016, pp. 1–5.

[20] R. Priyadharsini, T. Sreesharmila, Object detection in underwater acoustics images using edge based segmentation method, ICRTAC (2019).

[21] J. Rhinelander, Feature extraction and target classification of side-scan sonar images, in: 2016 IEEE Symposium Series on Computational Intelligence (SSCI), 1-6, 2016.

[22] S. Lee, B. Park, A. Kim, Deep learning based object detection via style-transferred underwater sonar images, IFAC-PapersOnLine 52 (21) (2019) 152–155, https://doi.org/10.1016/j.ifacol.2019.12.299, ISSN 2405-8963.

[23] S. Saravanakumar, N.K. Chandramohan, S.T. Prabakaran, M. Muniyappan, M. Shanmugam, V.S. Shaisundaram, The static structural analysis of torque converter material for better performance by changing the stator angle, Mater. Today:. Proc. 37 (2021) 1963–1972.

[24] S. Vijayjoshi, A.B. Kharate, A review: classification of sonar images using neural network approach, J. Emerg. Technol. Innov. Res. (JETIR) 6 (2) (2019) 327–331, ISSN-2349-5162.

[25] V.S. Shaisundaram, M. Chandrasekaran, S. Sujith, K.P. Kumar, M. Shanmugam, Design and analysis of novel biomass stove, Mater. Today:. Proc. (2021).

[26] Y. Song, B. He, P. Liu, T. Yan, Side scan sonar image segmentation and synthesis based on extreme learning machine, Appl. Acoust. 146 (2019) 56–65, https://doi.org/10.1016/j.apacoust.2018.10.031.

[27] M.S. Stoker, J.B. Pheasant, H. Josenhans, Seismic methods and interpretation, in: T.A. Davies, T. Bell, A.K. Cooper, H. Josenhans, L. Polyak, A. Solheim, M.S. Stoker, J.A. Stravers (Eds.), Glaciated Continental margins: An Atlas of Acoustic Images, Chapman and Hall, London, 1997, p. 315.

[28] S. Daniel, F. Le Leannec, C. Roux, B. Solaiman, E.P. Maillard, Side-scan sonar image matching, IEEE J. Ocean. Eng. (1998).

[29] Y. Song, Y. Zhu, G. Li, C. Feng, B. He, T. Yan, Side scan sonar segmentation using deep convolutional neural network, in: OCEANS 2017 - Anchorage, 2017, pp. 1–4.

[30] J. Yan, J. Meng, J. Zhao, Real-time bottom tracking using side scan sonar data through one-dimensional convolutional neural networks, Remote Sens. 12 (1) (2019) 37, https://doi.org/10.3390/rs12010037.

[31] Y. Xie, Machine learning for inferring depth from side scan sonar images, Degree project in computer science and engineering, Sweden 2019.

[32] Y. Chen, H. Niu, H. Chen, X. Liu, A Review of Underwater Target Recognition Based on Deep Learning, in: The 2nd International Conference on Computing and Data Science (CONF-CDS 2021), 1881 (2021) 042031 IOP Publishing, doi:10.1088/1742-6596/1881/4/042031, pp. 1–5.

[33] T. Yulin, S. Jin, G. Bian, Y. Zhang, Shipwreck target recognition in side-scan sonar images by improved YOLOv3 model based on transfer learning, IEEE Access 8 (2020) 173450–173460, https://doi.org/10.1109/ACCESS.2020.3024813.

[34] N.K. Chandramohan, M. Shanmugam, S. Sathiyamurthy, S.T. Prabakaran, S. Saravanakumar, V.S. Shaisundaram, Comparison of chassis frame design of Go-Kart vehicle powered by internal combustion engine and electric motor, Mater. Today:. Proc. 37 (2021) 2058–2062.

[35] P. Zhu, J. Isaacs, B. Fu, S. Ferrari, Deep learning feature extraction for target recognition and classification in underwater sonar images, in: 2017 IEEE 56th Annual Conference on Decision and Control (CDC), pp. 2724–2731, doi:10.1109/cdc.2017.8264055.

[36] Z. Zhang, Machine Learning for Inferring Side scan Images from Bathymetry and AUV Pose, Degree project in computer science and engineering Sweden, 2019.

[37] P. Vijayalakshmi, V. Rajendran, S. Arunthathi, P. Ganesan, D. Ravikumar, Performance analysis of a balanced-energy aware routing MAC protocol for underwater sensor networks, J. Crit. Rev. 15 (7) (2020) 4577–4586, https://doi.org/10.31838/jcr.07.15.611.

[38] E.N. Ganesh, V. Rajendran, D. Ravikumar, P. Sai Kumar, G. Revathy, P. Harivardhan, Detection and route estimation of ship vessels using linear filtering and ARMA model from AIS data, Int. J. Oceans Oceanogr. 15 (1) (2021) 1–10, ISSN 0973-2667.

Convolution Neural Network (CNN) Based Computerized Classification of Adulterated Fruits with SIFT and Bag of words (BOW)

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Abstract:

Most of the minerals and vitamins can be obtained by humans with the intake of fruits. Fruits are very rich in fibre and health-boosting oxidants can be provided by them. With a daily routine of eating fruits, a human can avoid the risk of diabetes, cancer, heart diseases. But these days fruits are being adultered for the [1] economic and technical benefits. Adulteration is a kind of illegal act of mixing some harmful chemicals into the fruits in order to increase profits. Eating adultered fruits can lead to chronic diseases diarrhoea, cancer, liver disorder, and heart diseases. Adulteration is a serious threat to the health of humans. Even though the adulteration of fruits is banned, many traders are applying adulteration in the thirst of more profits. It is very difficult to identify the fruits which undergone adulteration with naked eyes. Image processing techniques can be applied for detecting the adultered fruits. In this paper, A Convolution Neural Network (CNN) with K-means clustering and Bag of words based technique is proposed to detect the fruits which undergone adulteration. Accuracy of 0.94 is achieved with the proposed system.

Keywords: **Adulteration, Bag of words (BOW), CNN (Convolution neural Network), Detection, Diseases, Traders, K-Means clustering.**

I. INTRODUCTION:

According to the reports, in the entire world there are 2000 types of fruits are available. Fruits are very rich in fibre. Fruits are the main source of minerals and vitamins. Health boosting anti oxidants can be produced by the fruits, which makes a human to fight with many kinds of diseases. [2] An apple daily keeps doctor away which makes an human to be healthy. But these days, thee fruits are being adultered. Almost every food item in these days is getting adultered. Adulteration [3] is a process of

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mixing harmful. poor quality, substandard fruits to make fruits look more shining and fresh. There are few fruit business people who are adultering the fruits in the thirst for more money. The intention of fruits intake is for the nourishment of health which [4]is gained through them. Stages involved in fruits nourishment are production, then processing, and at last distribution of nourishment. Fruits are remained improved in terms of appearance, their texture, and hence the concept of adulteration came into practice. In the process of food adulteration, a fruit's quality gets reduced with the addition of chemicals to the fruits. Due to the addition of chemicals the appearance of fruits gets improved and hence these fruits can attract many customers to buy them and with this fruits can be sold for a huge amount. But the fact is with the consumption of adulteration fruits can cause serious health issues like cancer, heart-related diseases, and many diseases. Formalin is the chemical mostly used for the adulteration of fruits and the prevention of dead bodies from decaying can be done with the same chemical. The above reasons strongly suggest avoiding the fruit adulteration. Though the governments of countries are trying to restrict the fruit adulteration, this is not happening to the full extent. Image processing techniques can be applied to avoid this and the proposed model is shown in fig.1.

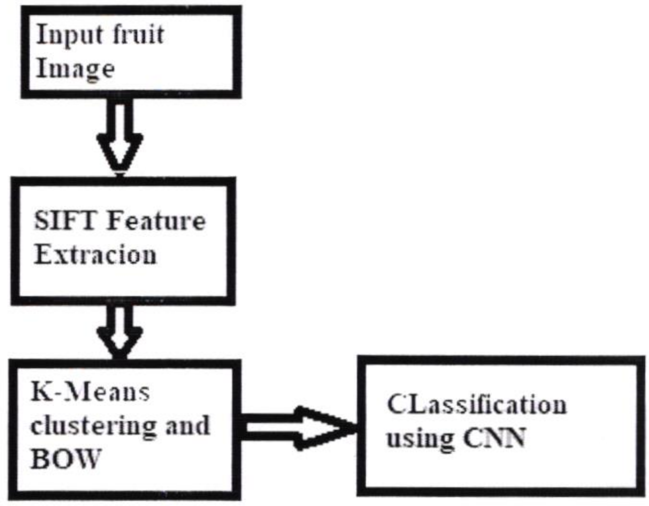

Fig.1 Proposed model

II. LITERATURE SURVEY

Food adulteration is a serious threat to the health of individuals [5] in any country. There are many kinds of adulterations are there. Common adulteration is done in milk, sweets, coffee, Dal, fruits, oils. Even the products which are[6] used for kids are being adultered and this affect a lot the health of kids and with this the kids gains unnecessary weights and also the diseases which has to be occurs[7] after 40 years of age. Sometimes food poisoning problems occurs with adultered fruits. Chemicals used for adulteration are carcinogenic, Metallic material like mercury, Artificial [8] ripening of fruits, metanil yellow, molasses sugar, aluminum, malachite green, ergot. Image processing techniques are very popular in health domain and food domains [9].Image processing techniques need filtering, clustering, and classification. Many filtering techniques [10] like mean, median filtering and m3 filtering techniques are popular for removing noise. PSNR values are used for noise check. Feature extraction techniques are much needed in the work of adulteration of foods.CNN classifier is [11] used for achieving higher accuracy.

III. Methodology

A. Dataset:

In the proposed model, it is necessary to have a good amount of dataset and the dataset is collected by using a Sony 16X zoom digital camera. Here 2000 samples of fruits are collected which are a combination of both normal fruits and adulteration fruits. Here fruits like apple, banana, mango, orange, papaya are taken into consideration where each kind of fruit in with 200 normal and 200 adulterations. And in the process of the experiment suggestions are taken from the fruit department regarding how the adulteration process goes

B.SIFT feature Extraction:

Scale-invariant feature transform (SIFT) is a feature extraction technique where portraying of 28 dimension vector is done at each and [12]every point. Detection of scale-space extrema is detected in the initial case. In the further steps detection of key point localization is done which further takes to the arrangement of extrema points to the key point descriptor. Working of feature extraction using SIFT can be seen in fig.2.

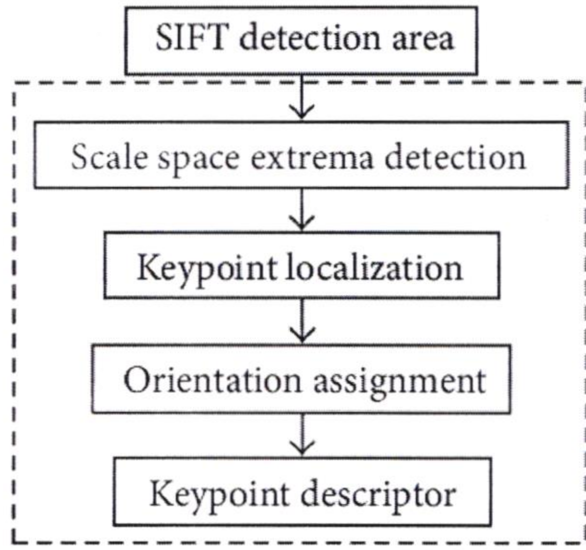

Fig.2 Step involved in SIFT

C. Feature clustering using K-Means:

Obtained feature are grouped into the clusters using K-Means clustering. In K-means clustering Euclidean distance [13] between the centroid and individual pixels is calculated and looping of the same process s done until all the pixels get clustered.Fig.3 shows the result of clustered pixels using the k-means clustering.

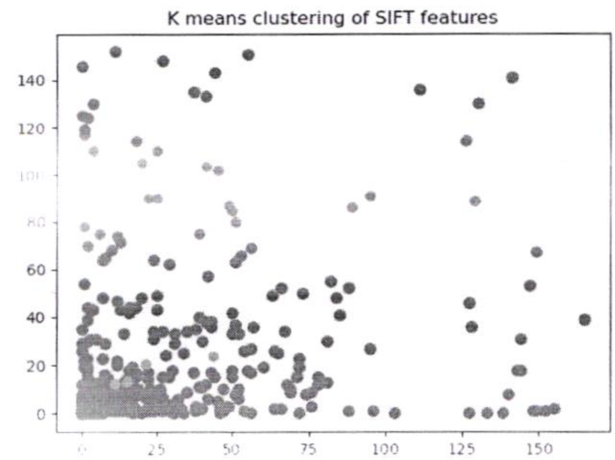

Fig.3 K-Mean clustering of SIFT features

D. Bag of Visual Words (BOVW):

BOVW is a technique that is being implemented in many areas and is the motivation for applying the same model in the [14] proposed work. And the results obtained with this are quite impressive and this boosted the accuracy of results. In Bag of visual words, all the clusters are considered as a word and all the words together are considered as vocabulary. And here each vocabulary is given as input for training purpose.Fig.4 shows the model of BOVW.

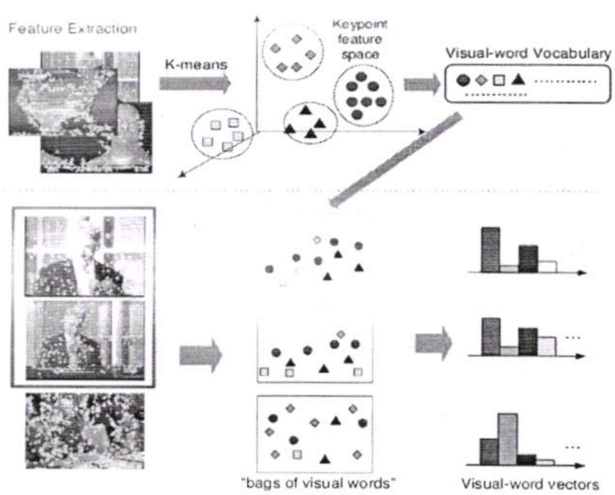

Fig.4 Model for Bag of Visual words

E.Classification using CNN:

Convolution neural network is the proposed classifier used for training and testing purposes. Here the image first gets resized [15] to optimal size. The resized image is given to the Convolution layer. Here each image is of 32X32X3 of pixel values. Here [16-18] dimensions of the kernel filter are 5X5X3. Here the [19,20] multiplication values are summed up for generating a single number which can be further used for sliding the kernel.Fig.5 shows the architecture of ANN.

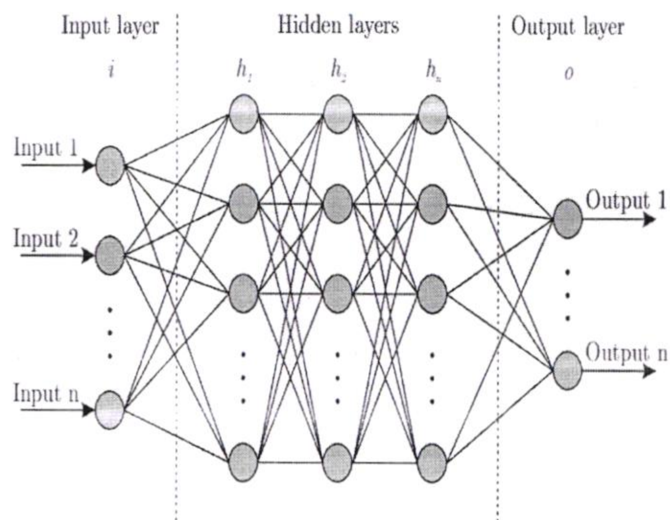

Fig.5 Architecture of ANN

IV. Results and Discussion:

Along with the CNN classifier few more classifiers are also taken into consideration for the work proposed. Other classifiers are probabilistic neural network (PNN), Back propagation neural network (BPNN), RBFNN (Radial Basis function Neural network), Support vector machine(SVM).Evaluation of work is done using Specificity, Sensitivity and Accuracy. Training is done with both kinds of fruit dataset which are normal and Adulterated Fruits.

$$Sensitivity = \frac{\mathrm{tp}}{\mathrm{tp} + \mathrm{fn}}$$

$$Specificity = \frac{\mathrm{tn}}{\mathrm{tn} + \mathrm{tp}}$$

$$Accuracy = \frac{\mathrm{tp} + \mathrm{tn}}{tp + fp + tn + fn}$$

Table.1 shows the performance evaluation of different classifiers. Here in proposed model with CNN model 93 % accuracy is achieved and also the accuracies of other classifiers are also considered and with CNN the highest accuracy is achieved.

	CNN	PNN	BPNN	RBFNN	SVM
Accuracy	93	88	84	88	82
Sensitivity	87	82	86	86	83
Specificity	91	83	89	87	86

Table.1 Comparison of results

Fig.6 shows the graphical representation of performance evaluation of different classifiers.

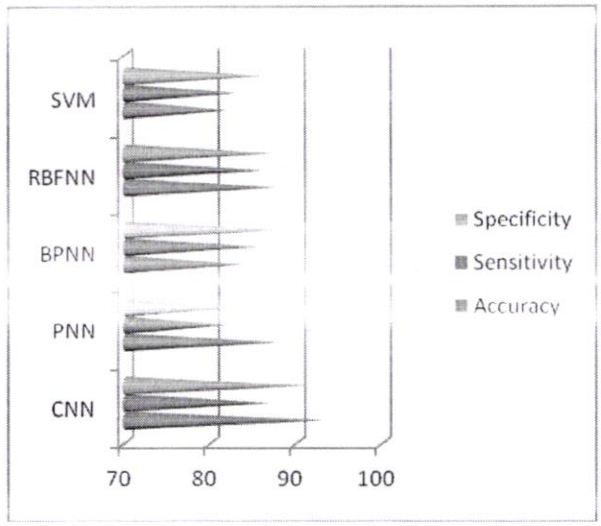

Fig.6 Graphical representation of performance evaluation

V. Conclusion:

In a mission of healthy India, where every individual should live healthy with less number disease, this proposed model helps in avoiding the intake of adulteration fruits. Proposed model achieves higher accuracy, which is better at present when compared to other models. Proposed model is tested for accuracy by applying other classification techniques like SVM, PNN, RBFNN, and BPNN. But the highest accuracy is achieved with CNN.

Future work:

This model is limited to detection of only adulteration fruits. This work can be further enhanced to classification of food items like adulteration sweets, ice and many more. Further accuracy of present model can also be enhanced by using other algorithms. Proposed model can also be enhanced with large amount of dataset.

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References:

1. H. Naskar, V. Nandeshwar and S. Das, "Adulteration Detection of Grape Fruit Juice Using PCA and LDA Pattern Recognition Technique," *2018 IEEE Applied Signal Processing Conference (ASPCON)*, 2018, pp. 83-86, doi: 10.1109/ASPCON.2018.8748633.

2. S. P. S. Brighty, G. S. Harini and N. Vishal, "Detection of Adulteration in Fruits Using Machine Learning," *2021 Sixth International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET)*, 2021, pp. 37-40, doi: 10.1109/WiSPNET51692.2021.9419402.

3. S. Patil, A. Abhishek, A. Prajapati and S. Das, "Automatic Detection of Orange Juice Adulteration using Constant Phase Element-based Impedance Sensor," *2018 4th International Conference for Convergence in Technology (I2CT)*, 2018, pp. 1-6, doi: 10.1109/I2CT42659.2018.9057952.

4. T. C. Trigoso, J. O. Cruz, H. A. Miñano and W. C. Silupu, "Application of Machine Learning in the Discrimination of Citrus Fruit Juices: Uses of Dielectric Spectroscopy," *2020 IEEE Engineering International Research Conference (EIRCON)*, 2020, pp. 1-4, doi: 10.1109/EIRCON51178.2020.9253756.

5. I. T. Haque and Y. Kohda, "Developing technology supported management approaches for reducing food safety problem based on Bangladesh," *2016 Portland International Conference on Management of Engineering and Technology (PICMET)*, 2016, pp. 2970-2978, doi: 10.1109/PICMET.2016.7806757.

6. S. R. V. G. K. M and L. J. K, "Intelligent Farming using Delta Robot," *2020 International Conference on Power, Energy, Control and Transmission Systems (ICPECTS)*, 2020, pp. 1-5, doi: 10.1109/ICPECTS49113.2020.9337002.

7. G. Giubileo, I. Calderari and A. Puiu, "High resolution spectroscopy of sweeteners," *2015 International Conference on Photonics, Optics and Laser Technology (PHOTOPTICS)*, 2015, pp. 85-90.

8. P. Neelakanteswara, D. Bharadwaja, P. Viswanath, C. Z. Basha and P. R. Savarapu, "Computer Based Advanced Approach for MRI Image Classification Using Neural Network With The Texture Features Extracted," *2020 International Conference on Smart Electronics and Communication (ICOSEC)*, 2020, pp. 195-201, doi: 10.1109/ICOSEC49089.2020.9215332.

9. A. Bekkanti, V. S. R. K. P. Gunde, S. Itnal, G. Parasa and C. M. A. K. Z. Basha, "Computer Based Classification of Diseased Fruit using K-Means and Support Vector Machine," *2020 Third International Conference on Smart Systems and Inventive Technology (ICSSIT)*, 2020, pp. 1227-1232, doi: 10.1109/ICSSIT48917.2020.9214177.

10. C. Z. Basha, G. Rohini, A. V. Jayasri and S. Anuradha, "Enhanced and Effective Computerized Classification of X-Ray Images," *2020 International Conference on Electronics and Sustainable Communication Systems (ICESC)*, 2020, pp. 86-91, doi: 10.1109/ICESC48915.2020.9155788.

11. C. K. Priya, M. Sudhakar, J. Lingampalli and C. Z. Basha, "An Advanced Fog based Health Care System Using ANN for the prediction of Asthma," *2021 5th International Conference on Computing Methodologies and Communication (ICCMC)*, 2021, pp. 1138-1145, doi: 10.1109/ICCMC51019.2021.9418248.

12. H. M. Al-Barhamtoshy and R. A. Younis, "DNA Sequence Error Corrections based on TensorFlow," *2020 21st International Arab Conference on Information Technology (ACIT)*, 2020, pp. 1-5, doi: 10.1109/ACIT50332.2020.9300094.

13. M. Shahzad, N. Alia and S. Mahmood, "DNA Innovate: Visualizing DNA sequences," *2009 International Conference on Information and Communication Technologies*, 2009, pp. 144-148, doi: 10.1109/ICICT.2009.5267200.

14. [M. Nuser and I. Alsmadi, "Evaluating graphical and statistical techniques for measuring similarity in DNA sequences," *2012 International Conference on Computer, Information and Telecommunication Systems (CITS)*, 2012, pp. 1-4, doi: 10.1109/CITS.2012.6220382.

15. Y. Yao, J. Ren, R. Bi and Q. Liu, "Bacterial Foraging Algorithm Based on Activity of Bacteria for DNA Computing Sequence Design," in *IEEE Access*, vol. 9, pp. 2110-2124, 2021, doi: 10.1109/ACCESS.2020.3047469.

16. S. Karimunnisa, V. Usha, A. Bekkanti and C. Z. Basha, "Advanced patient's Heart Rate monitoring system using Cloud based Android system," *2021 Second International Conference on Electronics and Sustainable Communication Systems (ICESC)*, 2021, pp. 293-298, doi: 10.1109/ICESC51422.2021.9532934.

17. S. Itnal, T. S. Rajeswari, C. Saxena and C. Z. Basha, "Advanced Automatic Human Emotion classification system with Lip Features Using M3 Filtering and Convolution Neural Network (CNN)," *2021 6th International Conference on Communication and Electronics Systems (ICCES)*, 2021, pp. 1287-1292, doi: 10.1109/ICCES51350.2021.9489202.

18. K. K. Kumar, S. Karimunnisa, A. Krishna, N. Cherukuri and C. Z. Basha, "An advanced approach for Smart Parking Solution Based on Ethereum Block chain System," *2021 Second International Conference on Electronics and Sustainable Communication Systems (ICESC)*, 2021, pp. 942-948, doi: 10.1109/ICESC51422.2021.9532882.

19. Tripathi, Milan. "Analysis of Convolutional Neural Network based Image Classification Techniques." Journal of Innovative Image Processing (JIIP) 3, no. 02 (2021): 100-117.

20. Chen, Joy Iong Zong, and Lu-Tsou Yeh. "Analysis of the Impact of Mechanical Deformation on Strawberries Harvested from the Farm." Journal: Journal of ISMAC September 2020, no. 3 (2020): 166-172