International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

# A Novel Fuzzy Neuro Deep Neural Network Model (FNDNN) for Classification of COPD Severity Levels.

[1]Charushila Patil, [2]Dr. Anita Chaware

**Submitted**: 20/11/2023 **Revised**: 29/12/2023 **Accepted**: 08/01/2024

**Abstract**: In recent years, there has been an increase in the mortality rate due to lung diseases like Chronic Obstructive Pulmonary Disease (COPD), and it is estimated that it will increase in upcoming years. The majority of deaths (80%) occurred in most of the nations having low and middle income hence, there is a need for a system that can help to reduce the mortality rate by providing proper treatment to the needy patient. Deep learning has shown outstanding performance in solving many real life problems in the healthcare domain. But it does not handle uncertain data. Its black box nature imposes restrictions on understanding its structure. In this study, a novel optimized fuzzy neuro deep-learning approach called FNDNN is proposed for classification. The main idea is the fusion of fuzzy logic and DNN model to deal with data uncertainty and rule extraction. To overcome overfitting of model different techniques like cross fold validation, changing learning rate is applied but the best result is achieved using L2 regularization. Pre-training and optimizing methods for learning parameters of the FNDNN are proposed. The proposed model for classification of COPD severity levels has better performance as compared with other classifiers as shown in results. This FNDNN model is very beneficial to the society and healthcare providers to accurately diagnose the severity levels of COPD and serve the emergency treatment to the needy one. .

***Keywords***: *Chronic Obstructive Pulmonary Disease (COPD), Spirometry, Deep Neural Network, Fuzzification, Defuzzification, Over fitting, Bayesian Regularization.*

## 1. Introduction

Despite the fact that COPD is a common, curable, and preventable ailment, the worldwide prevalence of COPD in adults (40 years of age or older) is 10.1%. Due to the fact that there were 3.23 million deaths worldwide in 2019, COPD was the third largest cause of mortality worldwide. According to a comprehensive study conducted by the World Health Organization (WHO) on COPD, it was estimated that the prevalence of the ailment increased by 68.8% between the years 1990 and 2010 in the Southeast Asia area. The number of people who have passed away has skyrocketed, going from 445 million instances to 751 million cases [1]. The percentage of people suffering from chronic respiratory disorders such as asthma or COPD who have been mistakenly diagnosed or misdiagnosed as having other respiratory diseases such as the common cold, acute bronchitis, or pneumonia [2–3]. The two most common types of chronic obstructive pulmonary disease (COPD) are chronic bronchitis and obstructive emphysema. According to the research [4,] the majority of individuals with COPD have a moderate form of the disease, whereas just 1% of patients have severe COPD and 1% have very severe COPD. The treatment of chronic illnesses has been shown to provide a number of significant obstacles, particularly in clinics that are not specialized in the field. It is challenging for people who require emergency therapy since the usual tests take a longer time to determine the severity level of COPD. Consequently leading to an increase in the proportion of COPD patients who pass away. As a result, there is an urgent need for the development of a system that can assist medical professionals in making precise diagnoses and providing timely treatment to those who are in need. The research presented in reference (5) demonstrates that modern technologies such as artificial intelligence, machine learning, the internet of things, deep learning, fuzzy theory, etc. are very useful for enhancing the performance of the system when used in conjunction with the pulmonary function test that is used the most, spirometry. The majority of systems, in order to effectively identify or forecast the outcomes, are constructed by fusing two or more distinct technologies together. Deep learning, often known as DL, is a kind of machine learning that use a multilayer model to learn more complex information and go beyond conceptual learning.

The second Deep neural networks are commonly used in the process of tackling difficult issues pertaining to artificial intelligence. However, because to the closed-source nature of DNN, there are some limitations placed on its application. Researchers came up with the fundamental idea of information extraction from neural networks in the form of rules to overcome this limitation of neural

*[1]Research Scholar,PG Department of Computer Science*
*PG Department of Computer Science*
*SNDTWU, Santacruz(w),Maharashtra,Mumbai*
*Asst.Professor ,Pratibha College,Chinchwad,Pune,Maharashtra,India*
*patilcharushila82@gmail.com*
*[2]Associate Professor ,PG Department of Computer Science*
*SNDT Women's University, Santacruz (w),*
*Mumbai, Maharashtra, India.*
*Anita.Chaware@computersc.sndt.ac.in*

networks. This approach is important for the knowledge representation of models. The vast majority of writers focus their attention on locating the rules that are the clearest cut; yet, these rules should also closely reflect the behavior of a neural network, which operates as a neuro-fuzzy system based on fuzzy rules.

The primary emphasis of this study is the incorporation of deep neural network (multilayer perceptron) components, which are vital to the process of developing and validating a network for COPD severity level categorization. Both the gathering of input data and the establishment of the rules for a deep neural network employ fuzzy logic.

Our contributions are as follows

In this study, we concentrate on classifying the COPD severity level from real-time data that contains ambiguity and uncertainty. In order to increase prediction accuracy, a combination of fuzzy logic and deep learning is used. The proposed model creates the FNDNN model by integrating DL with fuzzy representation to eliminate the Deep Neural Network's limitations of ambiguity in input data and rule extraction. The FNDNN model is then pre-trained and fine-tuned to classify COPD severity levels.

The steps of our research are as follows:

(1) FNDNN is developed for predicting the severity level of COPD. The fuzzy rules are generated adaptively utilizing the learning method of the FNDNN approach, which integrates fuzzy logic and deep neural networks. It investigates both fuzzy and deep representations to build additional characteristics while essentially resolving the uncertainty issue. Bayesian regularization is applied to overcome the overfitting of the model and get correct accuracy.

(2) A FNDNN model is based on the GOLD guidelines.

(3) Investigating the number of layers, neurons in the model, and activation functions leads to the optimum FNDNN structure. The FNDNN has strong prediction abilities.

(3) Using real time data of COPD patients at the YCM Hospital located in PCMC, Pune, Maharashtra, India, and the proposed approach is analyzed. The outcome confirms how well the suggested method performs when compared to other classification techniques.

(4) Rule Extraction to Improve Deep Neural Network Understanding

(5) Cross fold validation,early stopping L2 regularization is used to overcome overfitting of model.

The remaining part of this study is structured as follows: Focusing on Literature survey in Section 2. The system's components are presented in Section 3. The FNDNN model and associated learning method are suggested in Section 4. The results of the experiment are presented in Section 5. The study is concluded in Section 6, which also include future research work.

## 2. Literature Survey

In [8], Asaithambi used an adaptive neuro-fuzzy inference method to classify respiratory disorders using just spirometry data. The authors have attempted to use their neural fuzzy systems to estimate lung function using simply IOS or spirometry, as can be observed from the studies [6–8]. Meraz et al. [9] created software in 2008 for classifying pediatric respiratory diseases .Using extended RIC (eRIC) ,augmented RIC (aRIC) and IOS data, Hafezi [10] developed an integrated software solution for model-based on neuro-fuzzy classification of children's airway dysfunction in 2008. The first method for getting knowledge in form of rules from neural network model was the KT algorithm, which was introduced in [16]. The primary benefit of the Tsukimoto approach is that it has polynomial computational complexity as opposed to the exponential difficulty of the KT method [17]. In [18], a new approach to decision tree induction rule extraction was presented. Each output neuron of a neural network is transformed into a solution by their CRED method. Tree nodes are evaluated using nodes from a hidden layer, and leaves denote a class. The internal organization of the brain network is not considered in pedagogical methods. Most of the methods treat the Neural Network as a single unit like a "black box" [19]. Rule extraction is the key concept where directly mapping inputs to outputs is done [20].

## 3. System Components

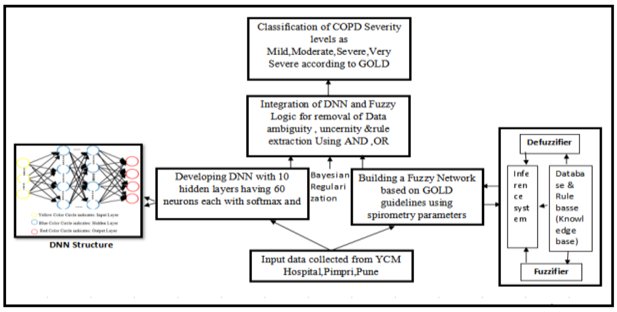


**Fig. 1:** System Diagram

Fig.1 shows detailed system diagram each system component explain in below section

*A. Representation of Fuzzy Logic*

Fuzzy logic is a set of mathematical rules for processing data with some degree of uncertainty or fuzziness. It enables for a more adaptable and appropriate strategy to be taken when analyzing data, especially when working with data that is in some way lacking in precision or certainty. Fuzzy logic represents knowledge in a way that makes it possible to deal with ambiguity by means of simple IF-THEN rules. Inconsistency in reasoning: representation as a useful tool for learning from incomplete or inconsistent facts. A fuzzy system consists of an input layer, a fuzzy layer, a rules layer, and a defuzzification layer. The input value is the sole thing that is passed on from the input nodes in a fuzzy logic system. The value of function should be the output of the single node in the fuzzy layer responsible for executing the membership function. Nodes in the input layer are linked to membership functions, and linguist labels are assigned to each input variable. In the rules layer, fuzzy logic rule matching is performed by means of links between nodes. Fuzzy logic operations, such as AND, are performed on the rule nodes. In the defuzzification layer, the results from the rules are combined using the OR operation. Adaptive fuzzy logic system, where a supervised learning approach is used to fine-tune the defuzzification process and associated rules. Fuzzy networks are employed in the proposed method for rule extraction from deep neural networks and to cope with unclear, ambiguous input.

*B. Deep Neural Network/Multilayer Perceptron*

The term "multilayer perceptron" (MLP) refers to a specific kind of feed-forward neural network that consists of numerous layers of perceptron. There is a distinct activation function associated with each of these senses. In MLP, the number of layers in the input and output representations are equal and they are coupled. Between these two levels lies a third one called the hidden layer. To kick off the MLP process, data must be given into the input layer. Each layer's neurons are connected to one another in a feed forward network. Each link between the input layer and the hidden layer is given a weight. To ascertain whether nodes are ready to contribute, MLP employs activation functions. Some examples of such activation functions include the tanh function, the sigmoid, and the ReLU. In order to provide the desired output from the supplied input set, MLP is usually employed to train the models and establish what sort of correlation the layers are providing. The model utilized in this work is a multilayer perceptron with 60-neuron hidden layers. Two common activation functions are ReLU and Softmax.

*C. Need of Integration*

Fuzzifying the deep representation occurs at the DL model's output layer in [11], after the original data has been fed into the hidden layer for pattern categorization. An innovative approach to machine learning, deep learning (DL) mimics the brain's cognitive method of processing information in a hierarchical structure, layer by layer. The intelligent automated finding of meaningful features from data is made possible by task-driven feature learning, which allows for sequential knowledge transmission from the lower levels to the top layers. Another discovery made by the fuzzy logic system [12, 13] is that it is possible to design membership parameters and fuzzy rules by learning from real data. With the addition of the fuzzy approach to DL, the effect of data uncertainty on system performance may be mitigated even further. Fuzzy rule extraction may be used to better comprehend how deep neural networks are built.

*D. Rule Extraction Algorithm*

Rule Extraction from Neural Network and rule-based learning techniques are two strategies used in artificial intelligence to solve classification issues. Both approaches are well-known iterations of researching models that forecast classes of data. NN rules-based training techniques excel in accuracy for many tasks. Nevertheless, neural networks have one significant disadvantage: they are less capable than rule-based methods of understanding what a trained concept model is. Because neural networks describe their notions using a vast number of parameters, they are challenging to comprehend [21]. The clarity and transparency of model increases by extracting rules. Identification of particularly crucial characteristics, or a component of comprehension, may include determining the reasons why neural networks make mistakes. The difference between accuracy and clarity in neural network models be eliminated using different methods for extracting rules [22–24]. The KT method, decision tree induction and the Tsukimoto polynomial method are mainly used for rule extraction. We employed a decision tree induction rule extractor layer as the rule extractor in our proposed system.

## 4. Fuzzy Neuro Deep Neural Network (Fndnn)

In order to classify the severity levels of COPD, we developed

the FNDNN model with the learning algorithm.

*E. Model of the FNDNN*

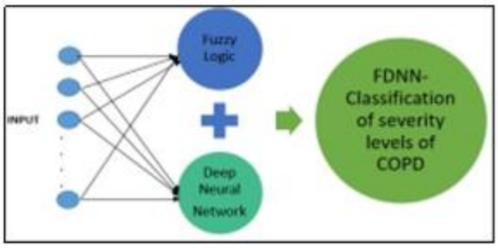


**Fig 2.** Model of the fuzzy deep neural network

Fig. 2 shows the proposed FDNN model. The input, the deep neural network (DNN), the fuzzy logic (FL), the rule extractor, and the classifier are the five components that make up the FDNN model. At first, input data flows over two different channels: the DNN for neural representation and the FN for fuzzy representation. Following the completion of these two modules' processing of the data, each epoch's findings from the FN and the DNN are combined, followed by the extraction of fuzzy rules and the classification of the COPD severity levels. By repeatedly minimizing the loss function value, model parameters can be adjusted in the FDNN training phase. By feeding the data into the model after it has been trained, the desired outcome can be reached.

*F. Mathematical construction of FNDNN*

- Fuzzy Network Model

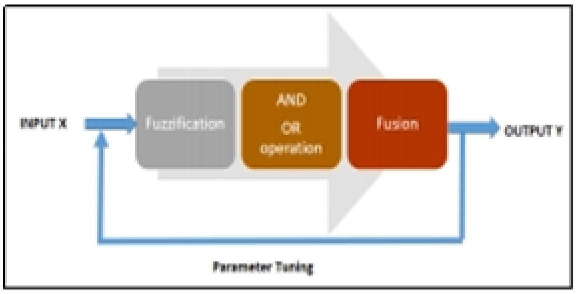


**Fig.4** Fuzzy Logic Structure

The organizational framework of the fuzzy network is shown in Fig. 4. Each node in the input layer is linked together in the fuzzification layer, and the membership function is used to calculate the input node's degree of membership in a given fuzzy set. Therefore, it is crucial to determine the membership function of a fuzzy network.

The FDNN strategy investigates fuzzy representation and deep learning for relearning [25] to capture the complex structure and high-level features of the data for prediction. Fuzzy and deep neural networks have been combined in the FDNN model.

Membership functions are designed based on GOLD guidelines as below

**TABLE 1** STAGES OF DISEASE

| **Parameters** | **Mild** | **Moderate** | **Severe** | **Very Severe** |
|---|---|---|---|---|
| FEV1 | > 80% | 80– 60% | 60- 40% | < 40% |
| FVC | > 80% | 80– 50% | 50- 30% | < 30% |
| FEV1/FVC | > 70% | 70% – 60% | 60- 50% | < 50% |

Table 1 shows the stages of disease based on the results of spirometry parameters. Stages in Table 1 are used as a knowledge base for rules.

One of the most widely used fuzzy operations in the layer of AND/OR operations is AND, which is represented as follows:

To make the fuzzy rules adaptable, the output of the nodes in the fuzzy layer is merged with the findings of the DNN component.

*G. MLP(DNN) Model*

The multilayer Perceptron (MLP) structure is used by the proposed fuzzy deep neural network to classify data. MLP's structure consists of neurons, weights, and activation processes, which are characterized as

$$F(y) = F(L) *F(L-1)$$

Where a is an activation function, w is the weight, and f(L) to f(L-1) are the input and output of the Lth neuron, respectively. Ten hidden layers with 60 neurons each are used in the suggested model.

After the entire network structure has been created, the network moves into the learning phase, where it adjusts the membership function parameters as well as the connection weights and biases. We use fuzzy theory and DL in the FDNN model to categorize the severity of COPD. The rule extraction layer uses a fusion approach as a result, which is determined by the COPD function.

The FNDNN model can be trained for multiclass classification by reducing the error or loss between the predicted value and the true value, ensuring that the inputs are correctly classified. Since the dataset for the proposed model is made up of mixed data, the reconstructed error is defined using the model's sparse categorical entropy loss function.nnThe FNDNN model must be trained through parameter initialization and fine-tuning prior to classification. A neural network may more effectively converge to a satisfactory local minimum with better setup. Parameter initialization in the FNDNN model encompasses both the FN and the MLP components. For ease of use, for initialization of weight w between each layer in the MLP component, the uniform distribution rule is used to initialize the weights. Every node's bias b starts at zero. The sum of the nodes in the final layer of the FN and DNN components is the same as the number of nodes in the rule extraction layer. The weights in each layer, the average value of the membership function, and the variance of the membership function's participation rate are all parameters that need to be set in the FN component of the system, and not in the layers themselves. The weights between the layer for "fuzzification" and the layer for "AND/OR operations" are both set to 1. The statistical method initializes the parameter, which can be found based on the mean value [14]. The FNDNN model is trained using the Adam approach and back propagation to fine-tune the parameters. The Adam approach works well for most non-convex optimization problems as well as big data sets and high-dimension spaces [15]. The parameter update process is performed later.

**Overfitting of model**

Underfitting and overfitting are common issues in machine learning models. Overfitting refers to a situation in which a model performs well on training data but fails on testing data or fresh data. Cross-validation, regularization, early halting, feature selection, etc. are only some of the methods that may be used to address this problem. We have employed cross-validation, early halting, and L2 regularization to prevent overfitting in the proposed model. L2 Regularization has shown to be the most effective method. In order to compute L2 regularization, we use informative distributions from the past and a small set of features ([26]). To find the optimal weight and refraction values for a network, L2 regularization uses Levenberg-Marquardt optimization to adjust the weight and refraction values based on minimizing error squares. In L2 regularization, network weights are added to the training goal function. The goal function is calculated using the following formula [28].

**Algorithm: FNDNN training Model**

Step 1: For FNDNN model take the input as $x_{0,} x_{1,...,}x_n$

Step 2: Initialize the parameters Θ = {w,b,u,c} and initialize learning rate

Step 3: Repeat

Step 4: Choose a batch of samples at random $_{\text{Cb from}}$ C.

Step 5: Calculate the triangular membership function and perform an AND or OR operation on input data to handle ambiguous data.

Step 6: Learn the training samples using the FNDNN.

Step 7: Determine the error L (Θ)

Step 8: Back-propagate the error in the FNDNN and update the parameters.

Step 9: Apply the L2 regularization to overcome overfitting.

Step 10: Till the stopping criteria is not meet, repeat steps 4 to 9.

Step 10: return back M (W, b, μ,c).

The above algorithm illustrates the step-by-step procedure for the construction and learning of FNDNN model.

## 5. Discussion and Results

The real time COPD data set is collected from YCM Hospital in Pimpri, Pune, Maharashtra, India as part of our creative approach. The data set contains 1500 records of COPD patients, which includes mixed data the features are Age,gender,smoking history, spirometry parameters Like FEV1,FVC,FEV1/FVC, MWT1,MWT2,MWTBEST, diabetes etc. The model is implemented in Python using the Keras and TensorFlow libraries. The data is preprocessed in such a way that incomplete and redundant data is removed and normalized the data. The splitting of the testing data and training data sets was done. As the data is mixed, like Categorical and integers, the loss function suitable for this data is sparse categorical cross entropy. For FNDNN model the Fuzzy logic is used to deal with uncertain and ambiguous data. Fuzzy rules are created based on GOLD guidelines .These rules are applied to the Deep Neural Network .But model has shown overfitting after integration of Fuzzy logic and Deep Neural Network. So to overcome overfitting of model different techniques such as cross validation, early stopping, pruning changing learning rate and Bayesian regularization are applied on dataset. Among this all techniques Bayesian regularization shows the desired result.

For evaluation of the model, the proposed model was compared with other classifiers like random forest, Decision tree, XGBOOST, KNN, etc. For analysis purposes, measures like accuracy, Precision, Recall, and F1 Score were used. Results show that our proposed model gives the better performance compare to all the classifiers

**The output of membership functions is shown in the following figures:**

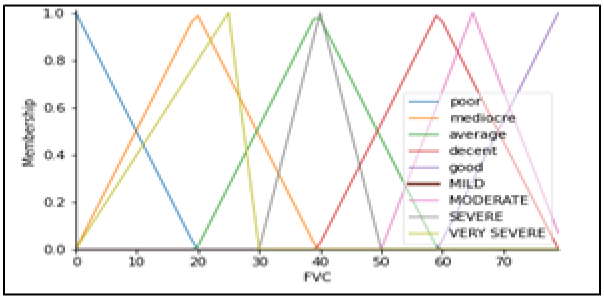


**Fig.5(a)** FVC (MILD)

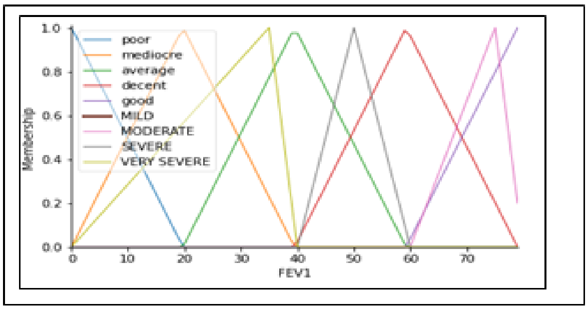


**Fig.5(b)** FEV1/FVC (MILD)

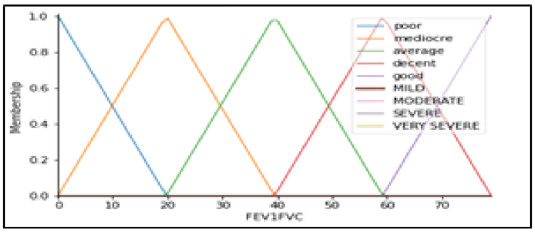


**Fig.5(c)** FEV1 (MILD)

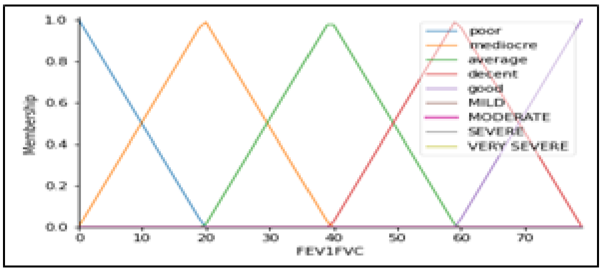


**Fig.5 (**d) FEV1/FVC (moderate)

**Fig. 5** (a) shows the triangular membership function for FVC (MILD). Fig. 5 (b) shows the triangular membership function for FEV1/FVC (MILD). Fig. 5 (c) shows the triangular membership function for FEV1 (MILD). Fig. 5 (d) shows the triangular membership function for FEV1/FVC (moderate). These all membership functions are based on (Global Initiative for Chronic Obstructive Lung Disease) GOLD guidelines.

**Fuzzy Rule Surface view for FNDNN**

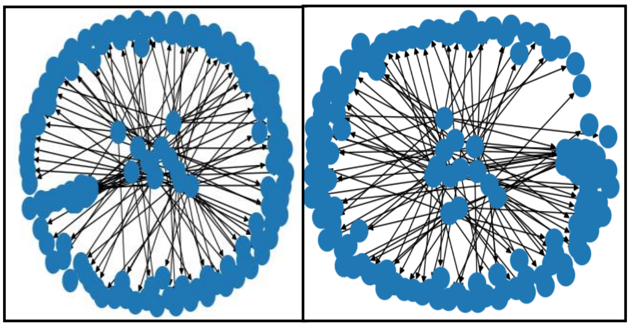

Fig.6(a) Fig.6 (b)

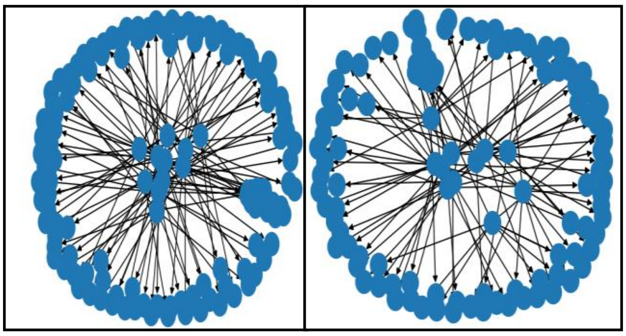

Fig.6(c) Fig.6 (d)

**Fig. 6**(a) shows the rule for prediction of MILD COPD as described as below

IF (FVC is mild) and (FEV1 is mild) and (FEV1/FVC is mild) and (MWT1is mild) and (MWT2 is mild) and (MWTBest is mild) and (Pack History is mild) and (CAT is mild) and (SGRQ is mild) THEN (COPD is mild)

Fig 6(b) shows the rule for prediction of MODERATE COPD as described as below

IF (FVC is moderate) and (FEV1 is moderate) and (FEV1/FVC is moderate) and (MWT1is moderate) and (MWT2 is moderate) and (MWTBest is moderate) and (Pack-history is moderate) and (CAT is moderate) and (SGRQ is moderate) THEN (COPD is moderate)

Fig. 6 (c) shows the rule for prediction of SEVERE COPD as described as below

IF (FVC is severe) and (FEV1 is severe) and (FEV1/FVC is severe) and (MWT1is severe) and (MWT2 is severe) and (MWTBest is severe) and (Pack-history is severe) and (CAT is severe)and (SGRQ is severe) THEN (COPD is severe)

Fig. 6(d) shows the rule for prediction of VERY SEVERE COPD as described as below

IF (FVC is very severe) and (FEV1 is very severe) and (FEV1/FVC is very severe) and (MWT1is very severe) and (MWT2 is very severe) and (MWTBest is very severe) and (Pack-history is very severe) and (CAT is very severe) and (SGRQ is very severe) THEN (COPD is very severe)

**Output of Defuzzification**

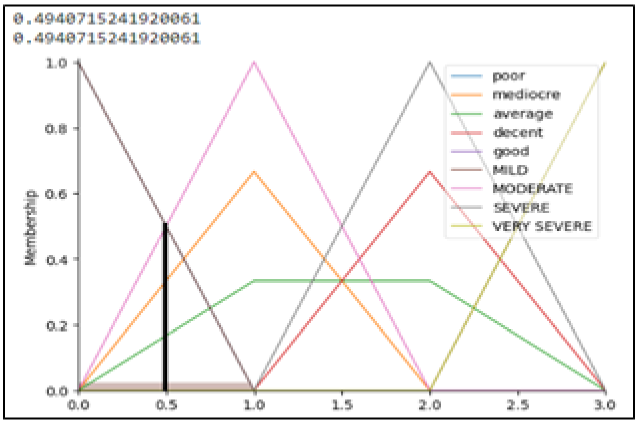


**Fig.7.**Defuzzification

Fig.7 shows Defuzzified output of Integrated FNDNN model.

**TABLE 2.** COMPARISION OF CROSS VALIDATION

| *N_splits* | *loss* | *Training acc.* | *Val_loss* | *Testing acc.* |
|---|---|---|---|---|
| 5 | 2.3276e-04 | 1.0000 | 2.6897e-04 | 1.0000 |
| 10 | 2.3276e-04 | 1.0000 | 2.6897e-04 | 1.0000 |
| 15 | 1.6278e-04 | 1.0000 | 1.9676e-04 | 1.0000 |
| 20 | 0.000 | 1.0000 | 0.000 | 1.0000 |

Table 2 shows the result of different cross validation applied on model overcome overfitting but the desired result is not achieved.

**TABLE 3.** COMPARISON OF CLASSIFIERS

| *Sr.No* | *Classifier used* | *Accuracy* | *Precision* | *Recall* | *F1 Score* |
|---|---|---|---|---|---|
| 1 | FNDNN with L2 Regularization | 0.96 | 0.96 | 0.96 | 0.96 |
| 2 | KNN | 0.77 | 0.77 | 0.77 | 0.77 |
| 3 | SVM | 0.80 | 0.80 | 0.80 | 0.80 |
| 4 | Decision Tree | 0.88 | 0.88 | 0.88 | 0.88 |
| 5 | Voting Classifier | 0.65 | 0.65 | 0.65 | 0.65 |
| 6 | Random forest | 0.85 | 0.85 | 0.85 | 0.85 |
| 7 | XGBOOST | 0.88 | 0.88 | 0.88 | 0.88 |
| 8 | Gaussian Naïve Bayes | 0.85 | 0.85 | 0.85 | 0.85 |

Table 3 shows a comparative analysis of Classifiers with FNDNN model, which shows that FNDNN has highest accuracy as compared to other classifiers

## 6. Conclusion and Future Work

As COPD is the leading cause of mortality worldwide. It very important to classify the severity levels of COPD immediately to provide the emergency treatment to the needy one. So in this paper, the FNDNN model has developed to classify COPD severity levels based on GOLD guidelines. The proposed model has integrated fuzzy logic and the Deep Neural Network to remove ambiguity in input data and extract Rules for better understanding the DNN. And to deal with overfitting Bayesian Regularization has applied to the model. The model evaluated the FNDNN model on a data set of 1500 COPD Patients from YCM Hospital, Pimpri, Pune, Maharashtra, India, and verified the performance of the FNDNN Results shows that the FNDNN model is more powerful in its representation capability than existing classifiers. The FNDNN has some challenges, like the optimized structure of the model. In the future, it will be interesting to deploy this model as an android mobile app with optimal structure, which will be very useful in emergency condition. With this app health care providers will easily track patients and provide the treatment.

**Acknowledgment**

The authors thanked the Dean of YCM Hospital, Pimpri, Pune, Maharashtra, India for giving permission for Data Collection. Dr.Dipali Gaikwad, Head of Respiratory Medicine Department, for her extensive and expert help with data preparation and guidance. The research presented in this paper is the result of project work carried out by the authors under the Vishveshwarya PhD scheme of the Ministry of Electronics and Information Technology, Government of India. We are grateful for the help given to us.

**ETHICAL DECLARATION & APPROVAL**

The authors have no conflicts of interest. Ethics approval was obtained from the Dean, YCM Hospital, Pimpri, Pune, Maharashtra, India, and the research ethics committee. There was no direct Interaction between the patients involved for this research.

## References:

[1] Jarhyan P, Hutchinson A, Khaw D, Prabhakaran D, Mohan S.," Prevalence of chronic obstructive pulmonary disease and chronic bronchitis in eight countries: a systematic review and meta-analysis.", Bull World Health Organ. 2022 Mar 1;100(3):216-230. doi: 10.2471/BLT.21.286870. Epub 2022 Jan 19. PMID: 35261410; PMCID: PMC8886252.

[2] Murray CJ, Lopez AD. ,"Alternative projections of mortality and disability by cause 1990-2020: Global Burden of Disease Study.", Lancet. 1997 May 24;349(9064):1498-504. doi: 10.1016/S0140-6736(96)07492-2. PMID: 9167458, 1997.

[3] Nielsen, K. G. & Bisgaard, H ," The effect of inhaled budesonide on symptoms, lung function, and cold air and methacholine responsiveness in 2- to 5-year-old asthmatic children.", American Journal of Respiratory and Critical Care Medicine 162, 1500–1506,2005.

[4] Anthonisen, N. R., & Wright, E. C. ," Bronchodilator response in chronic obstructive pulmonary disease.", The American review of respiratory disease, 133(5), 814-819,1986,

[5] Song TW,"Correlation between spirometry and impulse oscillometry in children with asthma." Acta Pediatr, 97:51-54, 2008.

[6] Barúa M, Nazeran H, Nava P, Granda V, Diong B.," Classification of Pulmonary Diseases Based on Impulse Oscillometric Measurements of Lung Function Using Neural Networks.", Proceedings of the 26th Annual International Conference of the IEEE EMBS San Francisco, CA, USA,2004

[7] Winkler J, Hagert-Winkler A, Wirtz H, Schauer J, Kahn T, Hoheisel G,"Impulse oscillometry in the

diagnosis of the severity of obstructive pulmonary disease. “, Pneumol, 63:266-75, 2009.

[8] Asaithambi M, Manoharan SC, Subramanian S.,”Classification of respiratory abnormalities using adaptive neuro fuzzy inference system.”, Int Inf and Database Sys Lecture Notes in Computer Science, 2012, 7198:65-73.

[9] Meraz E, Nazeran H, Goldman M, Nava P, Diong B.,” Impulse Oscillometric features of lung function: towards computer-aided classification of respiratory diseases in children.”, 30th Annual International IEEE EMBS Conference Vancouver British Columbia, Canada,2008.

[10] Hafezi N.,”An integrated software package for model-based neuro-fuzzy classification of small airway dysfunction.” ETD Collection for University of Texas, El Paso Paper AI1473869, 2009.

[11] S. Zhou, Q. Chen, X. Wang.,” Fuzzy deep belief networks for semi-supervised sentiment classification”, Neurocomputing 131, 312–322, 2014.

[12] Y. Deng, Z. Ren, Y. Kong, F. Bao, Q. Dai,” A hierarchical fused fuzzy deep neural network for data classification”, IEEE Trans. Fuzzy Syst.2016.

[13] J. An, L. Xinzhi, G. Wen,”Stability analysis of delayed takagi-sugeno fuzzy systems: a new integral inequality approach.”, J. Nonlinear Sci. Appl. 10 (4) 1941–1959, 2017.

[14] N.K. Kasabov, Q. Song, Denfis,”dynamic evolving neural-fuzzy inference system and its application for time-series prediction”, IEEE Trans. Fuzzy Syst. 10 (2) 144–154, 2002.

[15] D.P. Kingma, J. Ba,”Adam a method for stochastic optimization”, Comput. Sci. ,2014

[16] Fu, L.,” Rule generation from neural networks. Systems, Man and Cybernetics”, IEEE Transactions on, 24(8):1114–1124, 1994.

[17] Tsukimoto H., “Extracting rules from trained neural networks.” Neural Net-works, IEEE Transactions on, 11(2):377–389, 2000.

[18] Sato M. and Tsukimoto, H.,” Rule extraction from neural networks via decision tree induction. “, Neural Networks, Proceedings. IJCNN’01. International Joint Conference on, volume 3, pages 1870–1875, 2001.

[19] Tickle A. B., Andrews R., Golea, M., and Diederich, J., “The truth will come to light: directions and challenges in extracting the knowledge embedded within trained artificial neural networks.” IEEE Transactions on Neural Networks, 9(6):1057–1068, 1998.

[20] Thrun S. (1995): Extracting rules from artificial neural networks with distributed representations. Advances in neural information processing systems.

[21] Craven, M. and Shavlik, J. W. ,” Using sampling and queries to extract rules from trained neural networks”. In ICML, pages 37–45, 1994.

[22] Johansson, U., Lofstrom, T., Konig, R., Sonstrod, C., and Niklasson, L.,”.Rule extraction from opaque models–a slightly different perspective. In Machine Learning and Applications”, 2006. ICMLA’06. 5th International Conference on, pages 22–27.

[23] Craven, M. and Shavlik, J.,” Rule extraction: Where do we go from here?,” University of Wisconsin Machine Learning Research Group Working Paper, pages 99–108.1999.

[24] Sethi, K. K., Mishra, D. K., and Mishra, B.” KDRuleEx: A novel approach for enhancing user comprehensibility using rule extraction.”, In Intelligent Systems, Modelling and Simulation (ISMS),Third International Conference, pages 55–60,2012.

[25] J. Ngiam, A. Khosla, M. Kim, J. Nam, H. Lee, A.Y. Ng, “Multimodal deep learning”, in: Proceedings of the 28th International Conference on Machine Learning (ICML-11), 2011, pp. 689–696.

[26] E. Lázaro, C. Armero, and D. Alvares, “Bayesian regularization for flexible baseline hazard functions in Cox survival models,” Biometrical Journal, vol. 63, no. 1, pp. 7–26, 2021.

[27] R. Mbuvha, M. Jonsson, N. Ehn, and P. Herman, “Bayesian neural networks for one-hour ahead wind power forecasting,” in 6th International Conference on Renewable Energy Research and Applications, ICRERA, 2017, pp. 591–596.

[28] F. Burden and D. Winkler, “Bayesian Regularization of Neural Networks,” 2008, pp. 23–42.

[29] Pandey, J.K., Ahamad, S., Veeraiah, V., Adil, N., Dhabliya, D., Koujalagi, A., Gupta, A. Impact of call drop ratio over 5G network (2023) Innovative Smart Materials Used in Wireless Communication Technology, pp. 201-224.

[30] Anand, R., Ahamad, S., Veeraiah, V., Janardan, S.K., Dhabliya, D., Sindhwani, N., Gupta, A. Optimizing 6G wireless network security for effective communication (2023) Innovative Smart Materials Used in Wireless Communication Technology, pp. 1-20.