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Bipolar Neutrosophic Convolutional Neural Networks For Child Malnutrition Prediction Through Neutrosophic Set Domain.

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Abstract

Specifically, epistemic uncertainty, which reflects the model's lack of knowledge about the data, is the sort of uncertainty that has a significant impact on the performance of deep learning models employed for malnutrition prediction. The uncertainty in malnutrition dataset must be successfully resolved by enhancing deep learning architecture. To solve the issue of uncertainty information’s in malnutrition, Bipolar Neutrosophic Convolutional Neural Networks (BNCNN) is developed for extracting different deep features to generate predictive uncertainty estimates. A bipolar neutrosophic set is characterized by the positive-membership degree, where is a truth-membership function, indeterminacy-membership function, and falsity-membership function, and the negative-membership degree, where is a truth-membership function, indeterminacy-membership function, and falsity-membership function. Compared to Convolutional Neural Networks, the Bipolar neutrosophic is produced more accuracy results.

Keywords: Uncertainty, Neutrosophic, Prediction, Convolutional

I. INTRODUCTION:

Recent years the child malnutrition is the most important issue in the world. Today children’s are tomorrow futures for the world. Malnutrition problem can cause due to various reasons. From childhood itself children have malnutrition issues will lead more health issues in their future. Some economic issues, low family incomes, poor nutrition intake, poor sanitization, not aware about breastfeeding, anaemia in maternity period, poor maternity welfare facility and childhood disease these are the most common factors for child malnutrition issues. The prediction of child malnutrition will solve the health issues in advance and save the children from major health issues will lead in their future. In existing technique used machine learning and deep learning algorithm were used to predict the malnutrition status which has not been solved the uncertainty issues.

In fuzzy sets, true and false membership degrees only considered for classification. Uncertainty data point is not considered in classical fuzzy set. Recently many applications consider uncertainty data in classical set. The

traditional fuzzy set describes the membership degree with a real number [0,1][1]. So uncertainty is not considered in fuzzy set. In this case, sometimes the classical fuzzy cannot solve the related problems with uncertainty.
Neutrosophic set is used to deal with uncertainty, indeterminacy and inconsistent information. Neutrosophic set approaches are suitable to modeling problems with uncertainty, indeterminacy and inconsistent information in which human knowledge is necessary, and human evaluation is needed.
In real world problems for data mining, indeterminacy components may arise. Neutrosophic logic can handle this situation.
1.1 Working concept of Convolutional Neural Network:

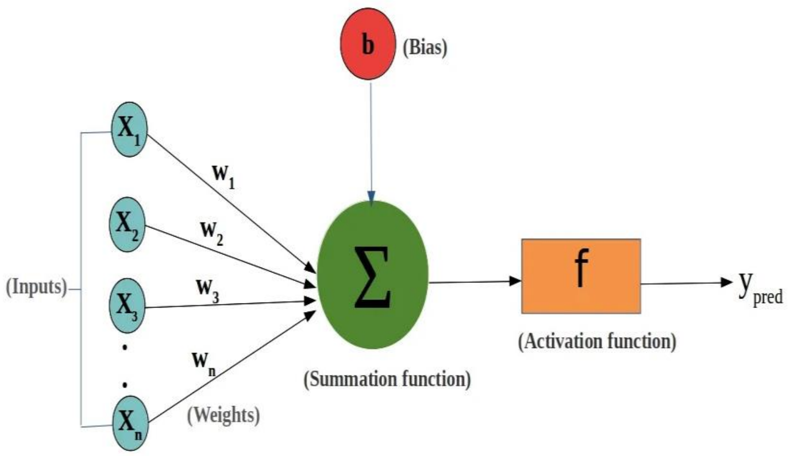


Fig 1. Basic building block of a neural network.

Fig. 1 represent the basic building block of neural network concept.Recently neural network concept widely used in various applications. Researcher found the Neural network concept based on human body neurons. Human body have a greater number of neurons so that the purpose of neuron is transmission of information from one body location to human brain. Neural network has developed based on this scenario.
In Neural network, data is passed to the input layer then the learning parameter of weight and bias can be added with input data after that data passed to the hidden layer and the hidden layer output is passed to the final output layer.
In Neural network, weight and bias are learnable parameters which is used to find the pattern in neural network data. In neural network process, every input parameter is passed to the separate neuron and find the permutation combination value in hidden layer for each neuron. In hidden layer every neuron learns the different king of patterns and pass that pattern to an activation function. The purpose of the activation function is normalizing the given data. Recent years Relu activation function is most probably used. Usage of activation function is reducing the volume of the data and find the nonlinearity in the given data. Based on nonlinearity find the loss in every iteration. The final output is not matched with the expected output that is($y \neq y'$) then again that the predicted loss value is passed to backpropagation method. In backpropagation, again new weight and bias values will be updated. The Backward propagation method work until the gradient descent error value is reached zero. The weight calculation is represented in (1).

New weight= Old weight $\pm \Delta\, d_E / d_{w11}$ -----> (1)

II. RELATED WORKS

In this research work[1] used CNN classification model and taken the input that is speech signals and their noisy data was considered as uncertainty in NS domain. In this proposed classification model is trained with uncertainty data and it provides more robust result in test data. Bosc and Pivert [2] introduced a study is called bipolar fuzzy relations where each tuple is associated with a pair of satisfaction degrees.
The neutrosophic set with deep learning achieve the better accuracy by using COVID-19 x-ray datasets[3]. The multi criteria decision making [4] which is used to solve the issues of uncertainty. The approach of multi criteria decision making is used to address the Issue of uncertainty. Decision maker established neutrosophic set with five different criteria for each patient which is used to determine which type of condition is mostly occurred.

The real-life application in medical diagnosis use the NS domain is carried out to solve various problem in disease prediction.[5]. The neutrosophic set in medical diagnosis is used to solve the uncertainty issues. Neutrosophy for Survey Analysis in Social Sciences [6] create membership function true, indeterminacy and false by using experimental data and produced better accuracy compared to fuzzy analysis. There are various factors were responsible for child malnutrition [7], so many of research work carried out to found most reasonable factors for child malnutrition.
The study [8] shows that the Neutrosophic convolutional neural network effectively handle noisy data with higher indeterminacy and results showed that the NCNN performs better than CNN models with noisy data.
A bipolar neutosophic multiple criteria decision-making concept [9] taken the attributes in the form of bipolar neutrosophic numbers and select the most desirable parameters. Later on, Lee extended the Fuzzy Set by introducing bipolar valued fuzzy sets [9] whose range of membership degree is augmented from the previous interval from 0 to 1 to the new one from − 1 to 1. Deli et al., in [10], introduced bipolar neutrosophic sets (BNSs). also addressed some characteristics, theorems, and aggregation operators of the BNS and executed them in an example of buying a car, from this analzsed results the bipolar neutrosophic set shown the better results.
Deep learning (DL) and neutrosophic techniques also used to improve the rate of computational medical image analysis [11]. Many theories can deal with ambiguous information such as para consistence logic theory [12], intuitionistic fuzzy set (IFS) theory [13], fuzzy set (FS) theory [14], probability theory [15]. One of these methods is the FS introduced by Zadeh (1965) which solves fuzziness and ambiguity problems that exist in medical data [16]. One disadvantage of FS that it doesn't take indeterminacy in its consideration independently [17].
Most probably medical data is partial, inaccurate and vague. Input system may vary in different kind of medical data research. Basically, large set of data can be handled in medical data analysis. So, in this situation indeterminacy, irregularity and vagueness must be solved. Human rational can solve the problem with ambiguity of knowledge. So neutrosophic can solve the problem with this ambiguity. Neutrosophy has the input parameters of truth, falsity, and an indeterminacy degree, which are independent of each other [18]. Neutrosophic logic has three components,T, I, F which is used to handle uncertainty issue by using extra domain indeterminacy(I)[19]. The research work [20] proposed a filter to remove noise from MRI image by converting into neutrosophic domain and then obtain neutrosophic membership value T, I, F then apply y-median filter to decrease indeterminacy.

III. PROPOSED WORK

Epistemic uncertainty refers to the uncertainty of the model and is often due to a lack of training data. Epistemic uncertainty is reducible with collection of more training samples from diverse scenarios. But, the datasets for malnutrition detection are only limited samples. In order to solve the uncertainty issues, Bipolar Neutrosophic Convolutional Neural Networks (BNCNN), is proposed for malnutrition prediction through neutrosophic set (NS) domain. Neutrosophic set (NS) is an extension of the fuzzy set that attempts to solve this problem by considering the truth, indeterminacy, and falsity memberships. For this task, the malnutrition features are firstly mapped from the feature domain to three sets true (T), indeterminacy (I) and false (F) in NS domain by the proposed method. Again, map the features into the Positive degree of Truth-membership, Positive degree of Falsity membership, Positive degree of indeterminate toward falsity and indeterminate towards truth membership, Negative degree of Truth-membership, Negative degree of Falsity membership, Negative degree of indeterminate toward falsity and indeterminate towards truth membership. Moving on to the Deep learning process, using positive and negative degree of membership values obtained.

Then, BNCNN with four parallel paths, two with the input of T and another two with the input of I, is constructed followed by an appropriate combination of paths to generate the final output. Here, four paths are trained simultaneously, and neural network weights are updated using back propagation algorithm. It may be worth mentioning that four paths are trained simultaneously in contrast with four-path structures in which each path is trained separately, and then, frozen weights are combined in the final step. In fact, in the first epoch of training, weights in four paths are updated simultaneously by multiplying the outputs of paths which leads to gradient switching. In this case, paths affect and help each other resulting in robust weight updates. The effectiveness of BNCNN to handle uncertainty in malnutrition dataset is proved by comparing conventional CNN models.
In the decision-making situation, the rating of performance values of the alternatives with respect to the attributes are provided by the decision maker in terms of bipolar neutrosophic numbers. The weights of the

attributes are determined using maximizing deviation method. In this work define bipolar neutrosophic relative positive ideal solution (BNRPIS) and bipolar neutrosophic relative negative ideal solution (BNRNIS). Working concept of Convolutional Neural Network is represented in Fig. 2 and Fig. 3 represented Rough Convolutional Neural Network Structure.

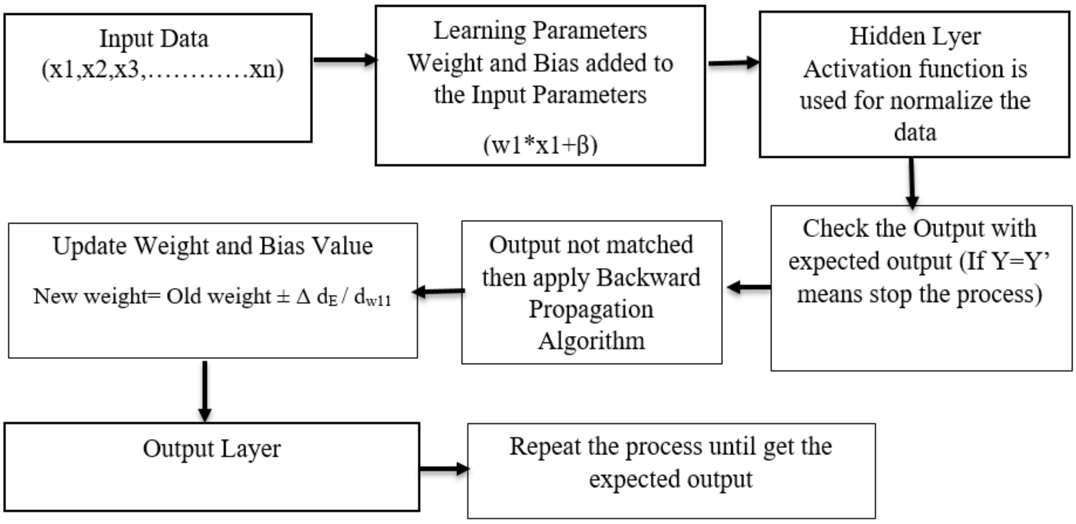


Fig2. Working concept of Convolutional Neural Network

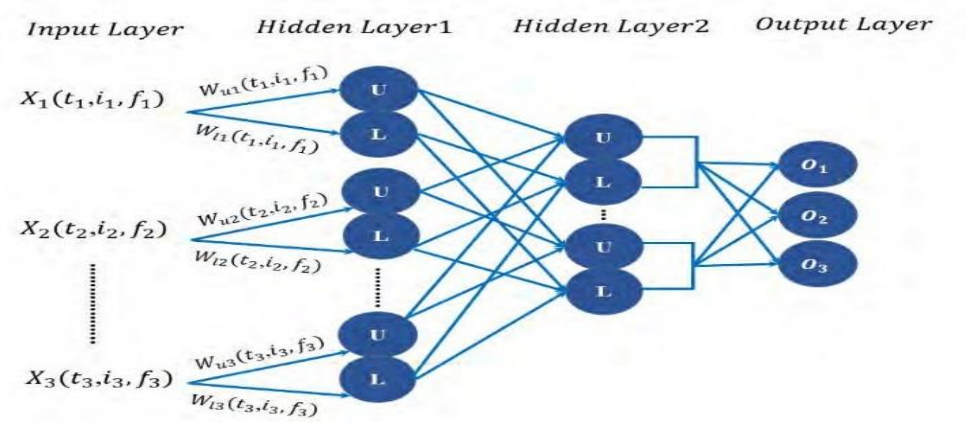


Fig 3. Rough Convolutional Neural Network Structure.

Input layer is composed of neuron for each data attribute. The output layer represents the five classes (normal, Overweight, stunting, Underweight and Wasting), the hidden layers rough neurons are determined by the Baum-Haussler rule (2).

$N_{hn} = N_{ts} \times T_e / N_i + N_o$ -----> (2)

Where Nhn is the number of hidden neurons, Nts is the number of training samples, Te is the tolerance error, Ni is the number of inputs (attributes or features), and No is the number of the output. During training process, the normalized input data is multiplied by its weight and computed ReLu activation function represented in (3).

ReLU formula:
f(x) = max(0,x) -----> (3)

If the function receives any negative input, it returns 0; however, if the function receives any positive value x, it returns that value. As a result, the output has a range of 0 to infinite.
Testing phase Classify new sample data and determine the accuracy rate of the model by using relation Accuracy = 1–absolute error, also calculate time consumption in model processing.

A. Classification Performance Analysis:
In order to evaluate the performance for each deep learning model in the malnutrition data, different metrics have been applied in this study to measure the true and/or misclassification of diagnosed disease in the tested data as follow. First, the cross-validation estimator was used and resulted in a confusion matrix as illustrated in Table 1. The confusion matrix has four expected outcomes as follows. True Positive (TP) is a number of anomalies and has been identified with the right diagnosis. True Negative (TN) is an incorrectly measured number of regular instances. False Positive (FP) is a collection of regular instances that are classified as an anomaly diagnosis FP. False Negative (FN) is a list of anomalies observed as an ordinary diagnosis.

Table 1. Confusion Matrix.

	Predicted Positive	**Predicted Negative**
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

After calculating the values of possible outcomes in the confusion matrix, the following performance metrics can be calculated.

Accuracy: Accuracy is the most important metric for the results of our deep learning classifiers, as given in (4). It is simply the summation of true positives and true negatives divided by the total values of confusion matrix components. The most reliable model is the best but it is important to ensure that there are symmetrical datasets with almost equal false positive values and false adverse values. Therefore, the above components of the confusion matrix must be calculated to assess the classification quality of our proposed framework.
Accuracy (%)=TP+TN / (TP+FP+TN+FN) -----> (4)

Precision: Precision is represented in (5) to give relationship between the true positive predicted values and full positive predicted values.
Precision=TP/ TP+FP -----> (5)

Recall: In (6), recall or sensitivity is the ratio between the true positive values of prediction and the summation of predicted true positive values and predicted false negative values.
Recall=TP / TP+FN -----> (6)

F1-score: F1-score is an overall measure of the model's accuracy that combines precision and recall, as represented in (7). F1-score is the twice of the ratio between the multiplication to the summation of precision and recall metrics.
F1-score=2($Precision \times Recall$ / $Precision + Recall$) -----> (7)

a. Backpropagation Algorithm
Supervised Learning: Backpropation is a supervised learning algorithm used for training artificial neural networks.
Objective: It aims to minimize the error between predicted outputs and actual targets by adjusting the network weights and biases.
Feedforward and Backward Pass: The process involves a feedforward pass to calculate the predicted outputs and a backward pass (backpropagation) to update the weights based on the error gradient.
Error Calculation: Backpropagation calculates the error or loss between predicted and actual output using a loss function.
Gradient Descent: It uses gradient descent optimization to adjust weights. The gradient of the loss function with respect to the weights is calculated and weights are updated in the opposite direction of the gradient to minimize the error.
Chain Rule: Backpropagation utilizes the chain rule of calculus to efficiently calculate gradients of the loss function with respect to the weights in each layer of the network.
Activation Functions: Backpropagation can be used with various activation functions (e.g., sigmoid, tanh, ReLU) in neural network layers, each having its impact on the gradient calculations.
Vanishing Gradient Problem: Backpropagation can face issues like the vanishing gradient problem, especially with certain activation functions, affecting the training of deep networks.

Learning Rate: Learning rate is a crucial parameter. It determines how much the weights are updated during each iteration. Too high a learning rate might overshoot the optimal solution, while too low might cause slow convergence. function (e.g., mean quared error, cross-entropy).
In this proposed work using this technique in implementing neural networks that allows to calculate the gradient of parameters in order to perform gradient descent and minimize the cost function.

Algorithm:
Step 1: Input X, arrive through the preconnected path.
Step 2; The input is modelled using true weights W, Weights are usually chosen randomly.
Step 3: Calculate the output of each neuron from input layer to the hidden layer to the output layer.
Step 4: calculate the error in the outputs
Backpropagation error=Actual Output- Desired Output
Step 5: From the output layer, go back to the hidden layer to adjust the weights to reduce the error.
Step 6: Repeat the process until the desired output is achieved.

a. Activation function:
It is used to determine the output of neural network like yes or no. It maps the resulting values in between 0 to 1 or -1 to 1 etc. (depending upon the function). The Activation Functions can be basically divided into two types- Linear Activation Function and Non-linear Activation Functions. The Nonlinear Activation Functions are the most used activation functions. It makes it easy for the model to generalize or adapt with variety of data and to differentiate between the output.
The Nonlinear Activation Functions are mainly divided on the basis of their range or curves. In this proposed work using ReLU (Rectified Linear Unit) Activation Function represented in (8). The ReLU is the most used activation function in the world right now. Since, it is used in almost all the convolutional neural networks or deep learning.
Equation: $f(x)= \max(0,x)$ and Range :Zero to infinity -----> (8)

C. Bipolar Neutrosophic Set:
A bipolar neutrosophic set is characterized by the positive-membership degree, where is a truth-membership function, indeterminacy-membership function, and falsity-membership function, and the negative-membership degree, where is a truth-membership function, indeterminacy-membership function, and falsity-membership function.
Let S be a universal set with a general element in S denoted by s; then, a bipolar neutrosophic set B in S is characterized by the positive-membership degree $T^+B(s)$, $I^+B(s)$, $F^+B(s)$, where $T^+B(s)$: $S \longrightarrow [0, 1]$ is a truth membership function, $I^+B(s)$: $S \longrightarrow [0,1]$ is an indeterminacy-membership function, and $F^+B(s)$: $S \longrightarrow [0, 1]$ is a falsity-membership function, and the negative-membership degree, where $T^-B(s)$: $S \longrightarrow [-1, 0]$ is a truth-membership function, $I^-B(s)$: $S \longrightarrow [-1, 0]$ is an indeterminacy-membership function, and $F^-B(s)$: $S \longrightarrow [-1, 0]$ is a falsity membership function. The proposed neutrosophic model is represented in Fig. 4.
The bipolar neutrosophic set B can be expressed as an object of the form:
$B=\{s, < T^+B(s), I^+B(s), F^+B(s), T^-B(s), I^-B(s), F^-B(s)> : s \in S\}$,
where $T^+B(s), I^+B(s), F^+B(s) \in [0, 1]$ and $T^-B(s), I^-B(s), F^-B(s) \in [-1, 0]$.

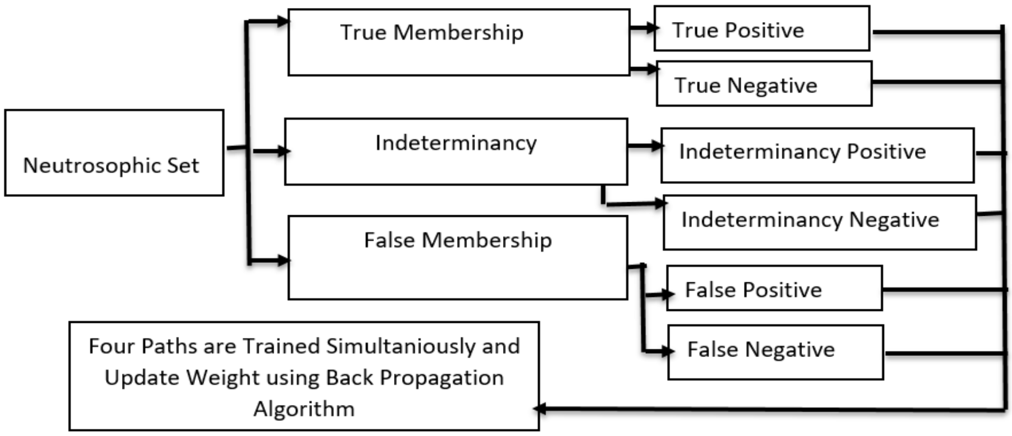


Fig 4. Proposed Neutrosophic Model

IV. COUNTS OF UNIQUE SAMPLES:

In this research taken benchmark dataset NFHS(National Family Health Survey)and various features (child age, weight, height, hemoglobin level, blood glucose,etc..) were considered to predict the child malnutrition status. This work considered totally 35655 samples such as normal counts 16047(46%), overweight counts 1376(35%), stunting counts 12336(3%), underweight counts 323 (1%), and wasting counts 5573(15%) and applied convolutional neural network classification to classify the data into five different classes namely normal, overweight, stunting, underweight, and wasting.

Here 24959(70%) sample data taken for train the model and 10696(30%) data applied for test the model. Fig 5 and 6 represented the result in the form of confusion matrix produced by Convolutional Neural network and Bipolar Neutrosophic Convolutional Neural network.

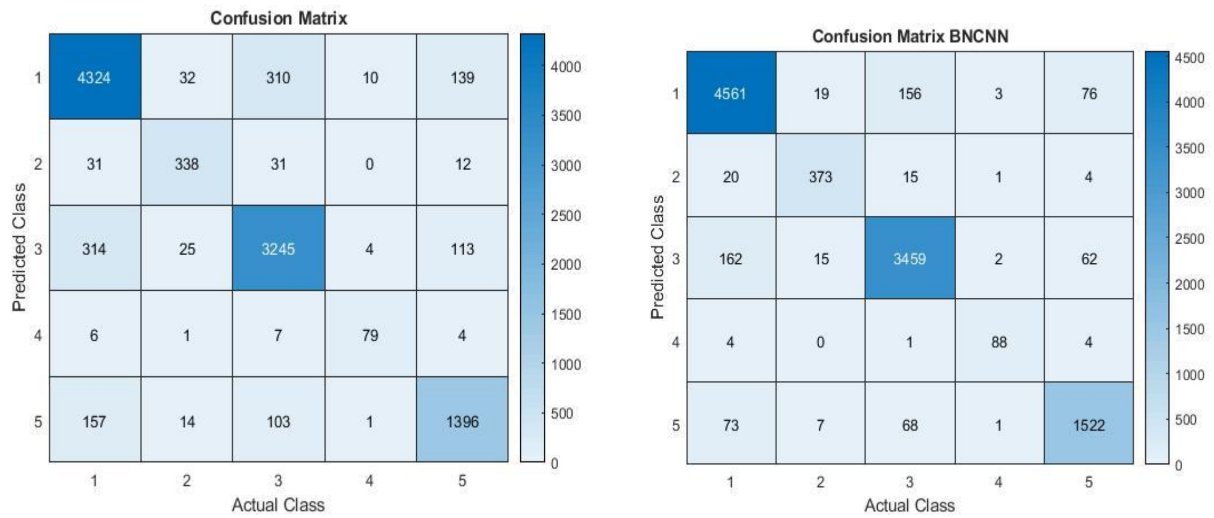


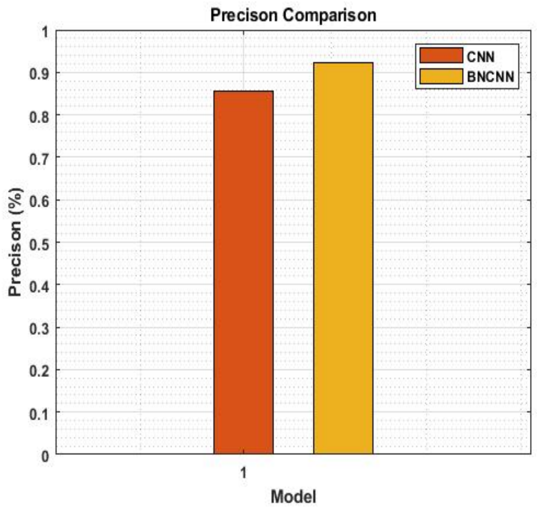
Fig 5. Confusion Matrix using Convolutional Neural networks

	predict_class1 Normal	predict_class2 Overweight	predict_class3 Stunting	predict_class4 Underweight	predict_class5 Wasting
Actual_class1	4561	19	156	3	76
Actual_class2	20	373	15	1	4
Actual_class3	162	15	3459	2	62
Actual_class4	4	0	1	88	4
Actual_class5	73	7	68	1	1522

Table 2. Confusion Matrix Output

	True Positive	False Positive	False Negative	True Negative
Actual_class1 Normal	**4561**	259	254	5622
Actual_class2 Overweight	**373**	41	40	10242
Actual_class3 Stunting	**3459**	240	241	6756
Actual_class4 Underweight	**88**	7	9	10592
Actual_class5 Wasting	**1522**	146	149	8879

Table 3. Multiclass Confusion Matrix Output



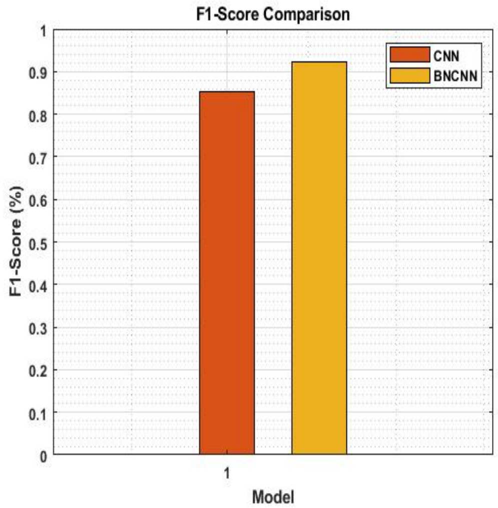
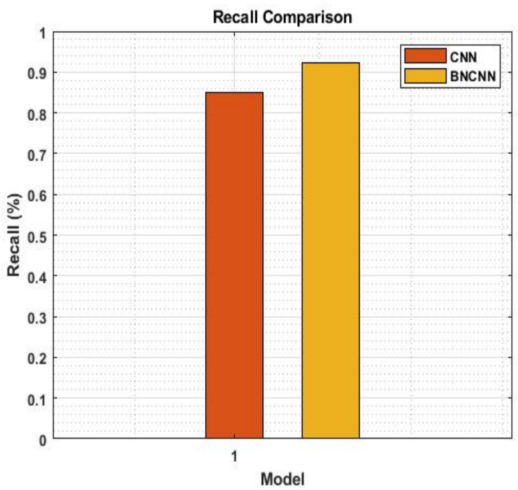


Fig6. Precision Comparison b/w CNN&BNCNN **Fig 7.** F1-Score Comparison b/w CNN&BNCNN

In this proposed work result Table 2 and 3 represented confusion matrix output and multiclass confusion matrix output. The Fig 7 to 10 represented the result of output metrices accuracy, Precision, Recall and F1-score between Convolutional Neural Network the bipolar neutrosophic convolutional neural network.

Compared to Convolutional Neural Network the bipolar neural network secured the accuracy 93.52%,Precision 92.42%, Recall 92.06% and F1-score 92.24%.



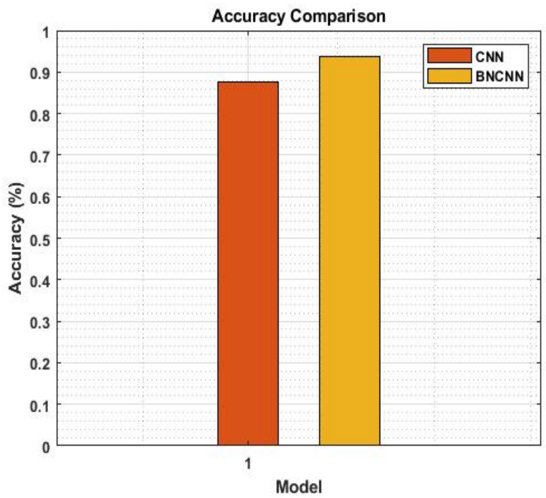


Fig 8. Recall Comparison b/w CNN&BNCNN **Fig 9.** Accuracy Comparison b/w CNN&BNCNN

V.CONCLUSION

Recent research work using deep learning model shows an effective impact in medical data analysis. This deep learning model performance can be improved via integration with neutrosophic system. Recently, the performance of deep learning model was affected by ambiguity or incomplete data, which are the major problems in medical data analysis. So, many researcher solve this issues by using neutrosophic logic.The proposed method of bipolar neutrosophic convolutional neural network in deep learning model is used to predict the child malnutrition status with more accuracy result. The existing method of convolution neural network cannot deal with uncertainty issues. The proposed method of BNCNN handled uncertainty issues. It is proposed for malnutrition prediction through neutrosophic set (NS) domain. Neutrosophic set (NS) is an extension of the fuzzy set that attempts to solve this problem by considering the truth, indeterminacy, and falsity memberships. In the proposed work taken child malnutrition data, 24959(70%) sample data taken for train the model and 10696(30%) data applied for test the model. This proposed work produced the result with accuracy 93.52%, Precision 92.42%, Recall 92.06% and F1-score 92.24%. In future will propose the model of feature ranking algorithm to rank the most import features to predict the better accuracy result.

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