FEATURE WEIGHTED BIPOLAR NEUTROSOPHIC CONVOLUTIONAL NEURAL NETWORK FOR PREDICTING CHILD MALNUTRITION

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ABSTRACT:

The uncertainty issues have happened in prediction of malnutrition status using a deep learning model. So, solve this uncertainty issues in deep learning model by enhancing the deep learning architecture. To solve the issue of uncertainty information's in malnutrition, Bipolar Neutrosophic Convolutional NeuralNetworks (BNCNN) is developed for extracting different deep features to generate predictive uncertainty estimates. In this bipolar neutrosophic set characterized by true positive, true negative, false positiveand false negative. This model used all setof features from the given dataset. So unimportant features also considered to predict the accuracy result. Whenever involved unimportant data, the model produced the result with less accuracy. In this proposed work using Regularization techniques to remove the less important features using weighted softmax algorithm and considered only subset of features from the given dataset and produce the more accuracy. Compared to Bipolar Neutrosophic Convolutional Neural Networks, the proposed model of the Feature weighted Bipolar neutrosophic model is produced more accuracy results.

Keywords: Malnutrition, Features, Bipolar, Regularization, Convolutional, Neutrosophic.

I. INTRODUCTION

Malnutrition, defined as insufficient or imbalanced nutritional availabilityresulting in negative changes in body composition and function, can develop as a result of inadequate intake, inflammation, hypermetabolism, or malabsorption. It is estimated that 15-60% of hospitalized patients are malnourished, although the diagnosis is frequently missed or delayed, resulting in avoidable bad consequences [1].

Child mortality and morbidity, under the age of five has its major cause as undernutrition. 90% of the total numbers of children who are underweight or suffering from stunting are from developing countries [2]. Malnutrition causes 41% of all the deaths of under five children.

Many hospital accrediting authorities, such as the Joint Commission, require malnutrition screening for all hospital patients. Most hospitals use questionnaires like the Nutritional Risk Screening or the Malnutrition UniversalScreening Tool, although there is no universal standard. These surveys frequentlyassess recent weight loss, BMI, acute illness effects, and nutritional intake. Screening questions are open to subjective interpretation [3], and many cases of malnutrition are missed [4]. As a result, malnutrition is frequently under-reported or unrecorded.

Early detection and treatment ofmalnutrition has a major impact on clinical, functional, and economic outcomes [5].Compared to non-malnourished patients,malnourished patients experience hospital admissions of twice the duration and cost. Malnourished inpatients have up to 4.7 times the mortality of the general inpatient population [6]. A malnourished patient is 1.6times more likely to be readmitted within 30days of discharge than a non-malnourished patient, and these readmitted patients are twice as likely to be diagnosed with a serious infection, compared to readmitted non-malnourished patients [7].

Proper diagnosis as well asintervention for malnutrition could lessen the risk for malnourishment. Variousmethods have been suggested in the literature for the automated identification of nutritional status of children. Linear discriminant analysis (LDA), k-nearestneighbors' (k-NN), support vector machines (SVM), RF, and logistic regression (LR) were used to predict malnutrition [8] status of children under 5 years. Further, ML algorithms such as random forest (RF), extreme gradient boosting and artificialneural networks have been used to predict the status of children's malnutrition [9]. However, ML algorithms have a limitation in that their model accuracy degrades with increasing input size.

Deep learning (DL) algorithms achieved superior performance in predicting children's malnutrition, compared to the MLmodel, supporting the feasibility of using artificial intelligence in nutrition research. DL approach may help to more accurately identify modifiable lifestyles variables at large scale, thereby clarifying opportunities for intervention to improve malnutrition prediction and public health. The longitudinal LSTM model produced the most accurate predictions of malnutrition [10] LSTM is a type of recurrent neural network which is used to extract temporal relationships between time-series data. A DL method was proposed [11] to predictmalnutrition based on pyridoxal 5′- phosphate (PLP) concentration.

However, malnutrition predictionusing ML and DL based approaches are having many

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restrictions to apply malnutrition datasets. This research analyzesthe problem occurred in the children’smalnutrition detection methods and proposed a novel solution to the identified problem.

II. RELATED WORKS:

Yin et al. [12] introduced a Tree based ML to visualize and validate a decision tool for identifying malnutrition in cancer patients. This model efficiently utilizes the Global Leadership Initiative on Malnutrition (GLIM) criteria which could beconveniently utilized to accelerate the pre- treatment identification of malnutrition in patients with cancer. The pre-treatment variables were used for the development of the decision tree and their individual associations with GLIM diagnosed Malnutrition. Finally, the DT algorithm was used to visualize and validate the performance to predict the malnutrition severity.

Shahriar et al. [13] developed a DL approach to predict malnutrition status of 0-59 month's older children. Initially, the dataset was collected from the Bangladesh Demographic and Health Survey 2014. The characterizing parameters like Weight-for-Age Z-score (WHZ) indicates for being wasting, Height-for- Age Z-score (HAZ) forbeing stunting, Weight-for-Age Zscore(WAZ) were widely applied to examine the magnitude of malnutrition as stunting, underweight and wasting respectively. Then,the features were extracted with primary sampling unit (PSU) to select individual child information. The data pre-processing stages was performed to remove the noise and string data form the collected dataset. Finally, the ANN with tensor flow was applied for the better malnutrition precisionsin children’s.

Lakshminarayanan et al. [14] utilizeda CNN model (AlexNet) to detect the malnutrition in children. In this model, the children affected with malnutrition with helpof their images and their parameter conditions like gender, age, weight and height are collected. Then, AlexNet model and Transfer Learning (TL) was trained using the image results and parametricconditions to identify the patterns in images to recognize faces and objects and performs classification tasks. The collected dataset is loaded as data folders and sub-folders. An appropriate learning rate, epochs and mini- batch values are given as input to the AlexNet structure. By utilizing the TLmodel with modified pre-trained network and mentioned parameters, it trains the entire network to classify the images for training so all the images get resized by using the re-sized function.

Gadekallu et al. [15] developed an identification of malnutrition and prediction of BMI from facial images using image processing and ML model. This modelutilizes a regression method based on the50-layers Residual network architecture to identify malnutrition affected people and obese people by analyze body weight and BMI from facial images. Then, a multi-task Cascaded CNN have been employed for the face detection. Gender-based analysis is performed for the prediction of BMI. Malnutrition and obesity were detected by utilizing the

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observed BMI value.

III. PROBLEM DESCRIPTION

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 and novel feature learning model.

The accuracy of training stage of DL based malnutrition prediction approaches is still low because of irrelevant set of attributes are used for training. This is improved by using only a candidate set of attributes used for training. Also, proper layers and mechanism can be introduced in DL models for capturing the minor details. Therefore, an efficient classification approach required to ensure Deep learningstability and improve its efficiency.

IV. RESEARCH OBJECTIVES

To solve the issue of uncertainty information's in malnutrition, Bipolar Neutrosophic Convolutional Neural Networks (BNCNN) is developed for extracting different deep features to generatepredictive uncertainty estimates.

To reduce the complexity of DL model, feature importance ranking algorithm and weighted Softmax models are proposed.

V. RESEARCH CONTRIBUTIONS

Epistemic uncertainty refers to the uncertainty of the model and is often due to a lack of training data. Epistemic uncertaintyis reducible with collection of more training samples from diverse scenarios. But, the datasets for malnutrition detection are only limited samples. In order to solve theuncertainty 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.

In this phase of work, a feature importance ranking algorithm is proposedand it will be added as a layer of CNN basedDL model. There is a lot of redundancy in feature maps from convolutional layers. So valid feature maps are selected by mutual information and others are abandoned whichcan reduce the complexity and computation of the network and do not affect theprecision. In this proposed technique, feature importance ranking algorithm helps for interpreting the model without performance decrease. It uses the DNN's inner dynamics to determine each feature's importance without the need of an external

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technique. It is an ad hoc technique that addresses the accuracy/ interpretabilitytradeoff. The proposed model assured that the importance of each feature is influenced by the interaction with other features, which does not occur in methods like random forest or mutual information. This also avoids situations in which weights have the same values. Furthermore, the use of the l1 norm, instead of the l2 norm, is based on theeffects of the L1 regularizations in the model related to feature selection. This configuration enforces the model to reach sparse solutions in which irrelevant features are tied to a weight value of zero. The use ofthe L1 would result in irrelevant featureshaving values close to zero. Additionally, imbalanced malnutrition classificationproblem is addressed using CNN with weighted softmax, which allowed learning of better features and avoidedmisclassification. The proposed model is named as Feature weighted BNCNN (FBNCNN).

Feature Selection:

It is the processing of selecting the subset of relevant features and leaving out the irrelevant features present in a dataset to build a model with high accuracy. Various methods are applied for feature selection like filter methods, wrapper methods and embedded methods. Here embedded methods solve the drawbacks of filter and wrapper methods. Embedded method isfaster than other methods and produce the more accuracy than others.

Implementation of embedded methods:

Set of all features à Consider subset of all featuresà Learning algorithm + performance.

Embedded methods using thetechniques of regularization. This approach of feature selection uses Lasso (L1 Regularization). In this method, penalty is applied to the coefficients, and bringing down some coefficient to zero. Finally, whatare all the features having zero coefficient, that can be removed from dataset.

L1 REGULARIZATION:

L1 regularization method can beused mostly for feature selection. In the working logic of L1 regularization is shrink the coefficient value as zero when the modelcan produce result in more variance and whenever involved unnecessary parameter, the lasso regression reduced unnecessary parameter with the coefficient value as zero.

Lasso regression only deploy an important feature in the model to improve an accuracy.

VI.DATASET DESCRIBTION

Indian NFHS Dataset (IDHS): The National Family Health Survey (NFHS) [16] is a large-scale, multi-round survey conducted ina representative sample of households throughout India. This dataset has districtlevel data. The latest one NFHS 5 was conducted between 2019 to 2021. Thesurvey is conducted by Ministry of Health and Family Welfare, Government of India, with the International Institute for Population Sciences serving as the nodal agency. National Nutritional Survey Dataset

: The National Health and Nutrition Examination Survey (NHANES) [17] is a program of studies designed to assess the health and nutritional status of adults and children in the United States. Neutrosophy has the input parameters of truth, falsity, andan 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]. Compared to themachine learning (ML) algorithms, the convolutional neural network (CNN) algorithm provides a better classification of the token IDs and provide better accuracy [20].

In this research taken 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. In this proposed model applied the technique of L1 regularization to remove the unwanted features and applied the dataset with relevant features such as (HAZWHO, WHZWHO, WEIGHT IN KG, SEX, WAZWHO, HEIGHT IN CM, TEST SALT IODINE, BP SYSTOLIC, VEGETABLESMONTH OR DAY, AGE, RURAL OR URBEN, HEMOGLOBIN LEVEL, BP DIASTOLIC, ETC ,..). In this proposed model used lasso regression to reduced unnecessary parameter with the coefficient value as zero.

Here 24959(70%) sample data taken for train the model and 10696(30%) data applied for test the model. Fig. 1 representedthe result in the form of confusion matrix produced by Feature Weighted Bipolar Neutrosophic Convolutional Neuralnetwork. In this proposed work result Table 1 and 2 represents, confusion matrix output and multiclass confusion matrix output.

VII.RESULTS AND DISCUSSION

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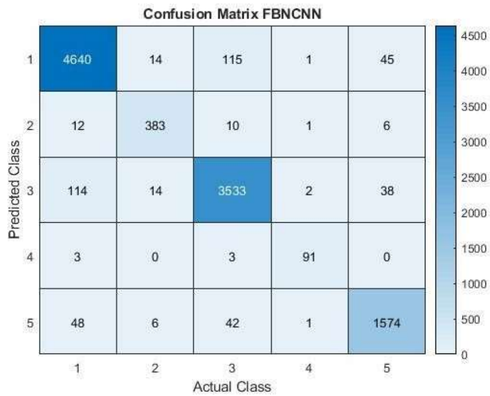

Table 1. Confusion Matrix Output

	True Positive	False Positive	False Negative	True Negative
Actual_ class1 Normal	**4640**	177	175	5704
Actual_ class2 Overweight	**383**	34	29	10250
Actual_ class3 Stunting	**3533**	170	168	6825
Actual_ class4 Underweight	**91**	5	6	10594
Actual_ class5 Wasting	**1574**	89	97	8936

Table 1. Multiclass ConfusionMatrix

	predict_ class1 Normal	predict_class2 Overweight	predict _ class3 Stunting	predict_ class4 Underweight	predict_ class5 Wasting
Actual_ class1	4640	14	115	1	45
Actual_ class2	12	383	10	1	6
Actual_ class3	114	14	3533	2	38
Actual_ class4	3	0	3	91	0
Actual_ class5	48	6	42	1	1574

Output F ig.1. Confusion MatrixRepresentation produced by FBNCNN, Table 2. Multiclass Confusion Matrix Output

Results Comparison With CNN, BNCNNand FBNCNN:

Table 3 represent that the results Comparison with Conventional NeuralNetwork, Bipolar Neutrosophic Conventional Neural Network and Feature Weighted Bipolar NeutrosophicConvolutional Neural network:

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MODEL/ METRICS	ACCURACY	PRECISION	RECALL	F1-SCORE
CNN	87.54%	84.66%	85.05 %	84.85 %
BNCNN	93.48%	90.74%	92.30 %	91.49 %
FBNCNN	95.59%	94.60%	94.55 %	94.58 %

Table 3. Results comparison with CNN,BNCNN and FBNCNN

VIII.CONCLUSION

Nowadays Various deep learningmethods are used to find out the better solution with high accuracy. This proposed model performance can be improved with the techniques of feature ranking algorithm L1 regularization. Implementation of datasetwith irrelevant features can decrease the model performance and error rate also can be increased. So that this proposed model used regularization techniques. The proposed method of Feature weighted 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 implementation of irrelevant features. The proposed method of FBNCNN handled these issues. It is proposed for malnutrition prediction through neutrosophic set (NS) domain with feature weighted ranking algorithm L1 regularization techniques. 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 95.59%, Precision 94.60%, Recall 94.55% and F1-score 94.58%. In future will propose the model of dove swarm optimizationtechniques to improve an accuracy and minimize the error.

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