RESEARCH PAPER

Comparative Analysis of Weighted Bayesian Belief Network and Fuzzy Weighted Bayesian Belief Network in Clinical Decision Support

Shweta Kharya*

*Bhilai Institute of Technology ,Durg, Chhattisgarh, India. shweta.kharya@bitdurg.ac.in

ABSTRACT

This technical paper presents a performance analysis of clinical decision support systems developed through a computational intelligence approach to address chronic diseases. The study explores two models, the Weighted Bayesian Belief classifier and the Fuzzy Weighted Bayesian Belief classifier, evaluated using established datasets, specifically the Heart Disease, Pima Indian Diabetics and Breast cancer datasets from the standard machine learning repository. The WBBN model is assessed for accuracy across diverse clinical datasets, achieving notable results in breast cancer of 97.18%, heart disease of 92.7%, and Pima Indian Diabetic dataset of 95.8%. Similarly, the FWBBN model exhibits superior accuracy, achieving 99% for breast cancer, 93.7% for heart disease, and 96.8% for Pima Indian Diabetic dataset. A comparative performance analysis with existing classifiers highlights the superior accuracy of the proposed models. Additionally, these novel models are compared with other Bayesian belief network models, demonstrating their effectiveness across various clinical datasets. The study concludes with insights into the future applicability of these models beyond clinical datasets and their potential in predicting survival probabilities based on different medical conditions.

KEYWORDS: Bayesian models, weighted concept, fuzzy weighted concept, clinical dataset, minimum Threshold.

How to cite this article: Kharya S. Comparative Analysis of Weighted Bayesian Belief Network and Fuzzy Weighted Bayesian Belief Network in Clinical Decision Support. Int J Drug Deliv Technol. 2026;16(69s):75-85. DOI: 10.25258/ijddt.16.69s.8

1. INTRODUCTION

The research conducted in current study involves the comparative study of two novel decision support system using a computational intelligence approach for addressing various chronic diseases. Two models, namely the Weighted Bayesian Belief Network (WBBN) and the Fuzzy Weighted Bayesian Belief Network (FWBBN), are explored within this paper. In this WBBN model, the traditional Bayesian classifier is rebuild to account for a key aspect of the clinical domain: "Not all symptoms carry the same importance for prediction," thereby enhancing its performance[1]. As each and every symptom has different impact on any illness in the clinical world[2]. And FWBBN has been proposed to incorporate another clinical dataset characteristic, i.e. "*Fuzziness in Clinical Data,*" by eradicating the Sharp boundary in clinical data [3]. An evaluation of these models is performed using established datasets, specifically the Heart Disease dataset [4][5][6], Breast cancer [7][8][9] and Diabetics Dataset[10][11][12]. The datasets are sourced from the UCI machine learning data pool, and its discretized form is obtained from Liverpool University (LUCS-KDD DN dataset), accessible through the following link: https://cgi.csc.liv.ac.uk/~frans/KDD/Software/LUCS-KDD-DN/DataSets/dataSets.html.

2. MODEL -1 :WEIGHTED BAYESIAN BELIEF NETWORK CLASSIFIER

This classifier is a predictive model which is reconstructed using conventional Bayesian network to fulfills one of the clinical dataset characteristics "*Not all symptoms carry the same importance for prediction* " .The overall the workflow diagram of novel model 1 is depicted in fig.1.

*Author for Correspondence: Shweta Kharya

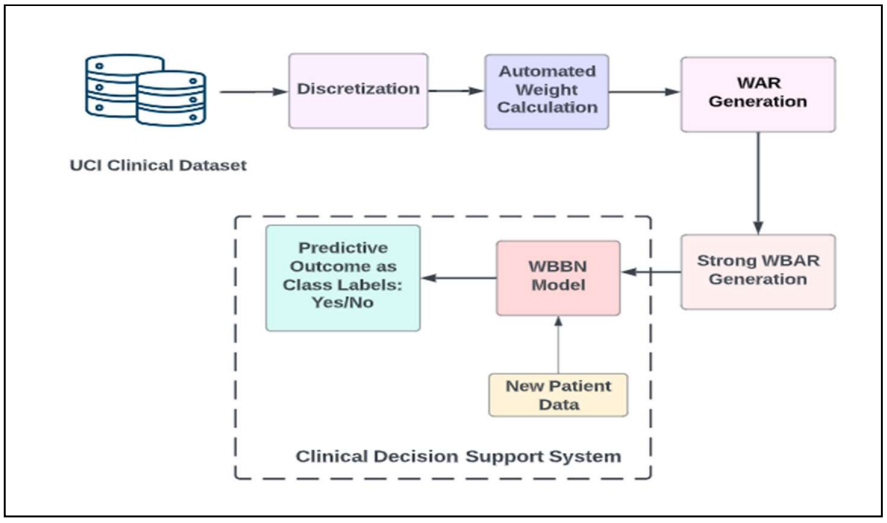

Fig.1.Workflow diagram of WBBN

The research follows the methodology illustrated in the workflow diagram to develop an intelligent system. As depicted in Fig. 1, the process begins with the application of an automated rank-based weight assignment technique to assign weights to attribute-value pairs. Next, rules are extracted based on weighted support and weighted confidence, covering associations between two attributes, multiple attributes, and their class relationships. This step generates Weighted Class_Association Rules (WAR). By further applying Bayesian concepts, such as weighted Bayesian confidence and weighted Bayesian lift, strong rules termed Weighted Bayesian Association Rules are derived. These rules are then used to construct the Bayesian model. Detailed formulas and algorithms, along with comprehensive explanations, are provided in recent publications[13],[14].

2.1 MODEL -1:WBBN EVALUATION ACROSS DIVERSE CLINICAL DATASETS

The assessment of the WBBN model involves an examination of strong rules and accuracy using clinical datasets. The outcomes are presented in Table 1, showcasing the WBBN model's performance across three clinical datasets: Breast cancer, Heart disease, and Pima Indian Diabetic (PIDD) datasets. Notably, the WBBN model, constructed with 5 strong rules from the breast cancer dataset, demonstrated a peak accuracy of 97.18%. This accomplishment was attained by training the model on 70% of the dataset and subsequently testing it on the remaining 30%, employing the designated Min_Threshold. [1][13].

The WBBN model, built using 7 robust rules from the Heart Disease dataset, achieves an accuracy of 92.7%. This outcome is derived by training the model on 70% of the dataset and testing it on the remaining 30%, using the specified Min_Threshold. Similarly, the WBBN model developed with 7 strong rules from the Pima Indian Diabetes dataset (PIDD) attains an accuracy of 95.8%. This result is achieved by training the model on 80% of the dataset and testing it on the remaining 20%, with the given Min_Threshold. The outcomes are visually represented in fig. 2.

Table 1. Evaluation of WBBN performance on clinical datasets

Data	**Threshold _ Minimum Weighted Support: Confidence**	**Distribution of Data Training :Test**	**Strong rules**	**Accuracy (%)**
Breast Cancer	36:70	70:30	5	97.18
Heart Disease	36: 70	70:30	7	92.7
Pima Indian Diabetic	40:80	80`:20	7	95.8

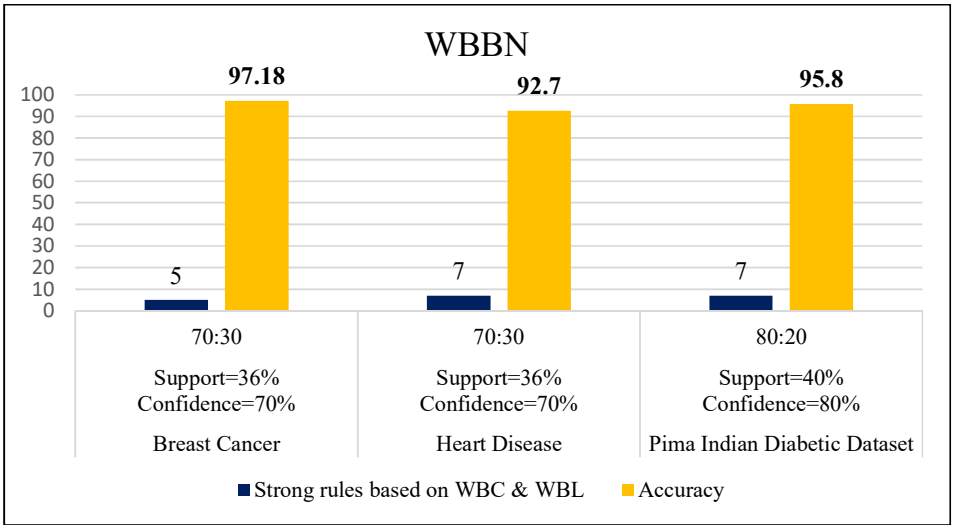

Fig 2. Assessment of WBBN performance across different Clinical Datasets

3. MODEL-2: FUZZY WEIGHTED BAYESIAN BELIEF NETWORK CLASSIFIER

The proposed classifier is a predictive model which is reconstructed using conventional Bayesian network to fulfills two characteristics of the medical dataset i.e. " *Not all symptoms carry the same importance for prediction " and "Fuzziness in Clinical Data,"* .The overall the workflow diagram of novel FWBBN model is detailed in fig. 3.

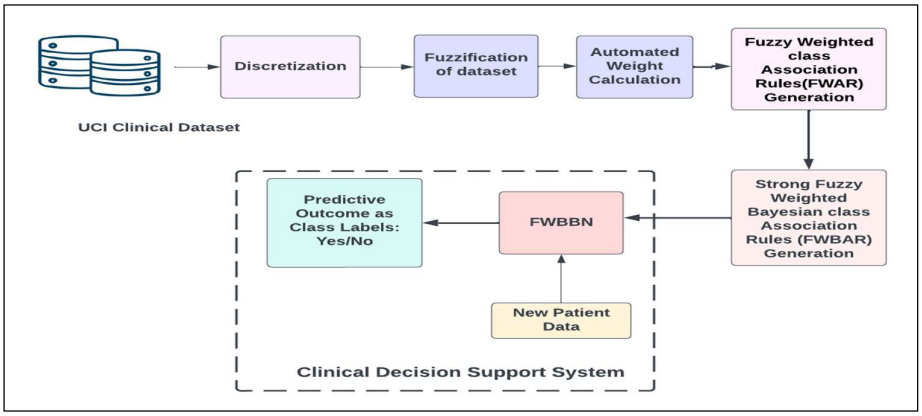

Fig 3.Workflow diagram of FWBBN model

The workflow of the proposed FWBBN research is illustrated in fig. 3, outlining the steps followed throughout the study. Initially, the dataset is retrieved from the UCI Machine Learning Repository, provided in a normalized format and accessed through LUCS-KDD DN software. Following the discretization process, the data is partitioned using fuzzy linguistic values, which are calculated through the fuzzy membership function. Weights are then determined using the Maximum Likelihood Estimation Method. Subsequently, Fuzzy Weighted_Class Association Rules (FWAR) is generated using FWS and FWC. The FWBBN model is constructed using strong rules derived from Fuzzy Weighted-Class Bayesian Association Rules (FWBAR). Detailed explanations of the formulas and algorithms are provided in the paper [3].

3.1 ASSESSMENT OF FWBBN MODEL PERFORMANCE ACROSS A RANGE OF CLINICAL DATASETS

Focusing on the results of the FWBBN model, an evaluation was conducted based on the number of strong rules and accuracy. The findings, summarized in Table 2, highlights the FWBBN model's performance across three clinical datasets: Breast Cancer, Heart Disease, and Pima Indian Diabetes (PIDD) datasets. Notably, the FWBBN model, developed using 5 strong rules from the Breast Cancer dataset, achieved an accuracy of 99%. This performance was attained by training the model on 70% of the dataset and testing it on the remaining 30%, using the specified Min_Threshold. [3].

Table 2. Evaluation of FWBBN performance on clinical datasets

Data	Threshold_ Minimum Fuzzyweighted Support:Confidence	Data Distribution Training :Testing	Strong rules	Accuracy
Breast Cancer	36:70	70:30	5	99%
Heart Disease	36:70	70:30	7	93.7%
Pima Indian Diabetic Dataset	40:80	80:20	7	96.8%

Similarly, the FWBBN model, utilizing 7 strong rules from the Heart Disease dataset, achieved an accuracy of 93.7%. This result was obtained by training the model on 70% of the dataset and testing it on the remaining 30%, using the specified Min_Threshold. Likewise, the FWBBN model built with 7 strong rules from the Pima Indian Diabetes dataset (PIDD) recorded an accuracy of 96.8%. This outcome was accomplished by training the model on 80% of the dataset and testing it on the remaining 20%, following the given Min_Threshold. A visual representation of these results is provided in Fig. 4.

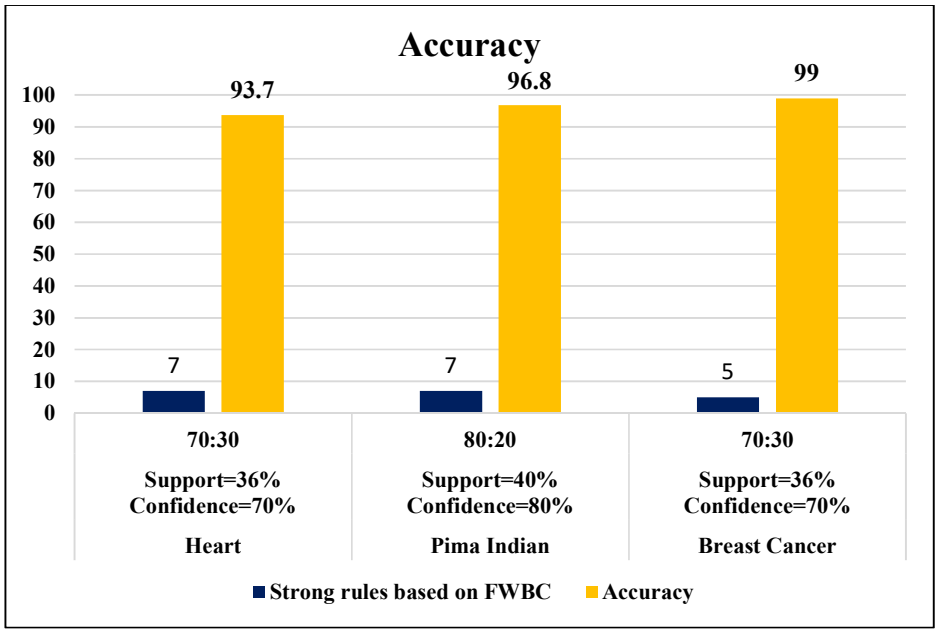

Fig 4. Results of FWBBN on various clinical datasets

4. PERFORMANCE EVALUATION OF WBBN OTHER PREDICTIVE MODELS

Using the same dataset the result of the proposed model is compared with popular classifiers. Table 3 illustrates the results obtained by proposed model with various state-of-the-art systems.

Table 3 WBBN_BreastCancer accuracy comparison with other classifiers

Data	Models	Accuracy
Breast Cancer Dataset	**WBBN(Proposed Model)**	**97.18%**
	Naïve Bayes[15]	95.99%
	SVM[16]	96%
	MLP NN[17]	91.19%
	k-NN[18]	96.00%
	Random Forest[19]	96.24%
	Decision Tree [20]	92.26%

This analysis reveals that the proposed model and approach achieved superior accuracy compared to other predictive models for the Breast Cancer dataset.

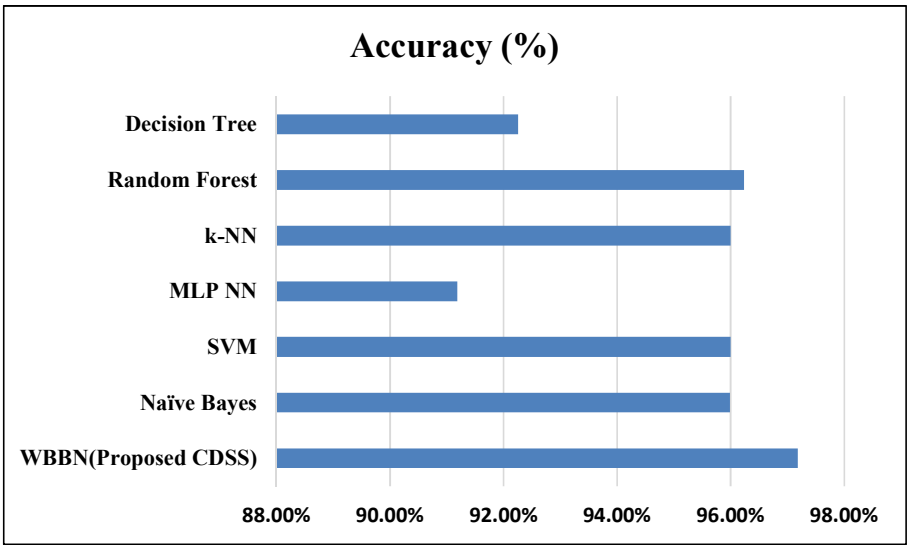

Fig 5. WBBN_BreastCancer comparison with other classifiers

To enhance the clarity of the comparison, a graphical representation has been generated, depicted in fig 5. Furthermore, the constructed WBBN model is juxtaposed with another pre-existing model across diverse clinical datasets, specifically the Heart disease dataset (Table 4) and the Pima Diabetic dataset (Table 5). Additionally, visual aids in the form of graphs are incorporated to augment the presentation of results, illustrated in fig 6 and fig 7 for the respective datasets.

Table 4. WBBN_HeartDisease accuracy comparison with existing classifiers

Data	Models	Accuracy
Heart Disease Dataset	**WBBN(Proposed Model)**	92.7%
	Naïve Bayes[21]	89.77%
	SVM[22]	84.12%
	MLP[23]	74%
	ANN ([24]	86.91%
	Decision Tree[25]	88%

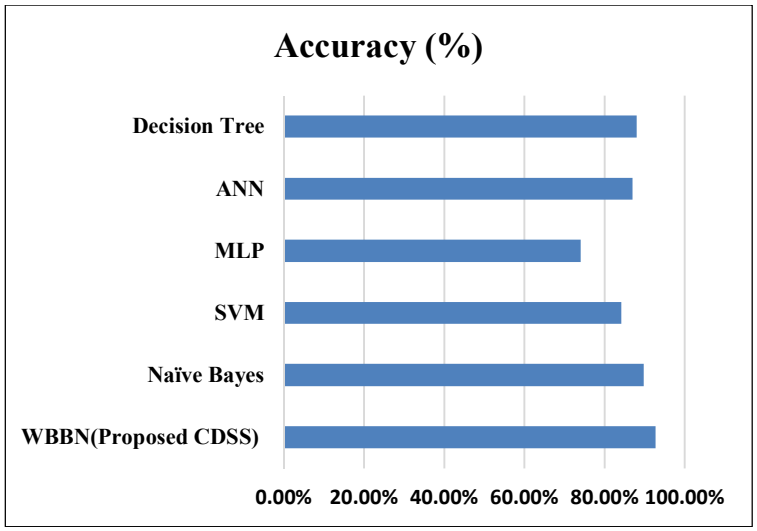

Fig 6. WBBN_HeartDisease comparison with other classifiers

Table 5. WBBN_Diabetic accuracy comparison with existing classifiers

Data	Models	Accuracy
Pima Indian Diabetic Dataset	**WBBN(Proposed Model)**	95.8%
	Naïve Bayes[26]	80%
	SVM[27]	94.5%
	MLP[28]	86.08%
	ANN[12]	91%
	Decision Tree[29]	82.14%

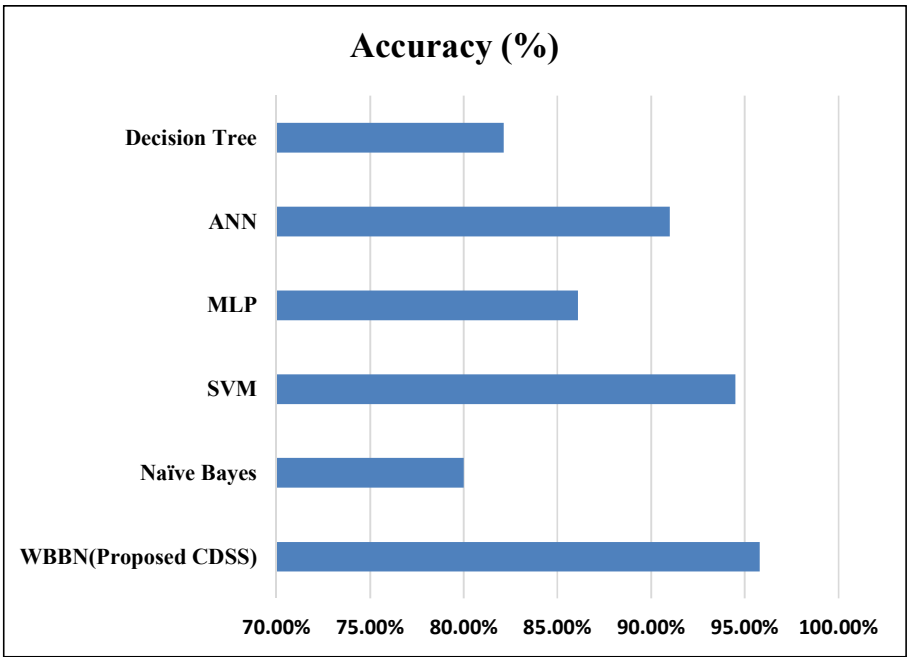

Fig 7. WBBN_Diabetic comparison with other classifiers

To provide a clearer observation and visualization, a graph has been created for all three datasets, showcasing the performance of various established classifiers, including Random Forest , Bayes classifier, SVM, MLP-NN, K-NN, , and Decision Tree, which are widely used in the medical field. The analysis highlights that the proposed WBBN model surpasses these classifiers in performance.

5. PERFORMANCE ANALYSIS OF FWBBN WITH OTHER PREDICTIVE MODELS

In the case of the second developed model, FWBBN CDSS, the comparison is exclusively conducted with existing fuzzy-based classifiers. This choice is made considering that FWBBN inherently demonstrates superior accuracy compared to other classifiers in recent research, including WBBN. To further assess FWBBN, a comparative analysis is carried out against fuzzy-based classifiers, utilizing clinical datasets such as breast cancer, heart disease, and Diabetics from the UCI machine learning repository. The results are presented in Table 6, Table 7, and Table 8, aligning with recent research benchmarks. Additionally, fig 8, fig 9, and fig 10, respectively are used to showcase the enhanced graphical visualization of the outcomes.

Table 6. FWBBN_BreastCancer accuracy comparison with other classifiers

Data	Model	Accuracy
Cancer	**FWBBN (Proposed CDSS)**	99%
	Neuro-Fuzzy model	95.14%[30]
	Fuzzy Temporal rule-based model	99%[9]

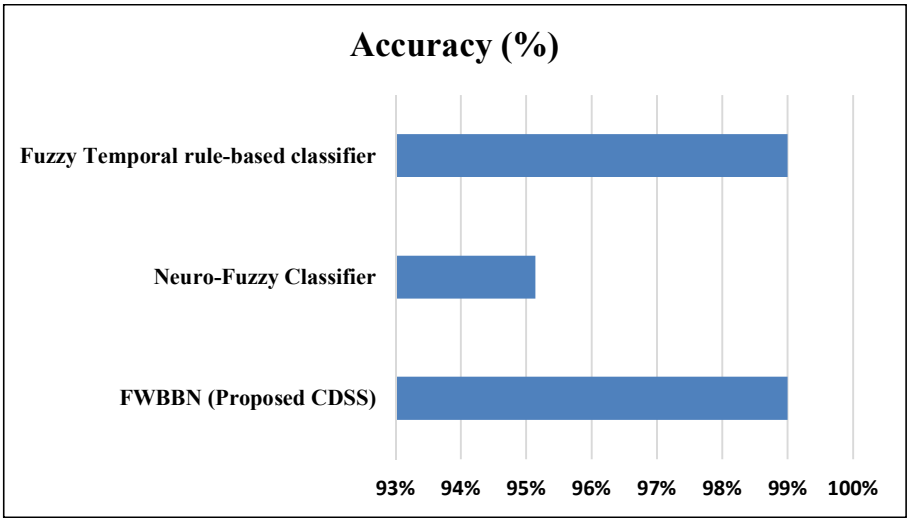

Fig 8. FWBBN_BreastCancer comparison with other classifiers

Table 7. FWBBN_HeartDisease accuracy comparison with other classifiers

Data	Model	Accuracy
Heart Disease	**FWBBN (Proposed CDSS)**	**93.7%**
	Fuzzy Random Forest	93.4%[31]
	Adaptive Weighted Fuzzy Rule-based system	92.13%[32]

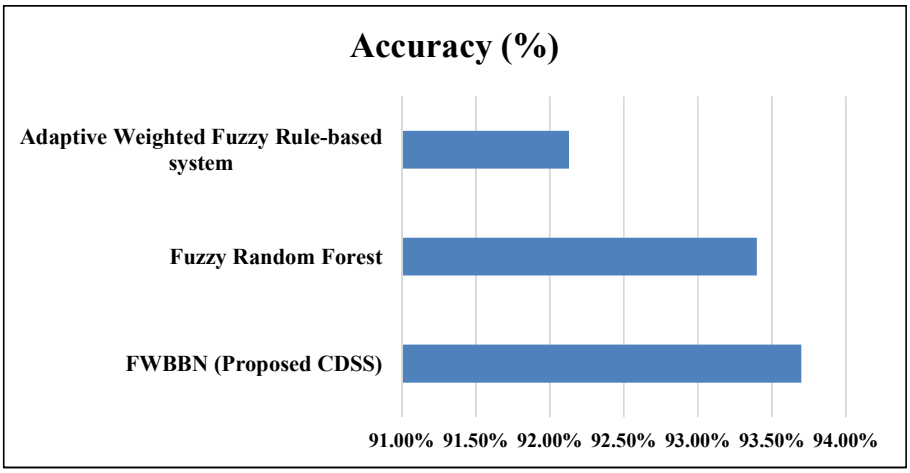

Fig 9. FWBBN_HeartDisease comparison with other classifiers

Table 8. FWBBN_Diabetic accuracy comparison with other classifiers

Data	Model	Accuracy
Pima Indian Diabetics Dataset	**FWBBN(proposed CDSS)**	**96.8%**
	Fuzzy KNN Classifier	90.63%[33]
	Fuzzy SVM	96.8%[34]

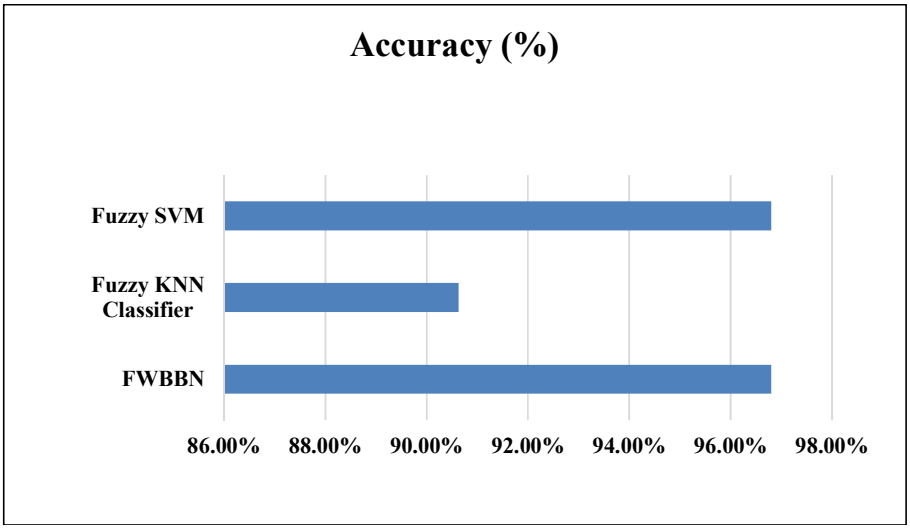

Fig 10. FWBBN_Diabetic comparison with other classifiers

6. PERFORMANCE ANALYSIS OF WBBN AND FWBBN WITH EXISTING BBN MODELS

The outcomes of the developed predictive models, WBBN and FWBBN, are subjected to a comparative analysis with existing Bayesian belief networks across the identical set of three clinical datasets. The resulting accuracies are summarized in Table 9 for various datasets.

Table 9. Results of FWBBN and WBBN with existing Bayesian Network classifiers on various datasets

Models	Breast Cancer Data	Heart Disease Data	Pima Indian Diabetic Data
FWBBN	**99%**	**93.7%**	**96.8%**
WBBN	**97.18%**	**92.7%**	**95.8%**
Existing Bayesian Networks	97.13% [35]	84% [36]	92.2%[37]
	96.49%[38]	95%[39]	82.48%[40]
	87%[41]	-	-
	97.1%[8]	-	-
	96.31%[42]	-	-

In this section, the accuracy of both the WBBN and FWBBN models on the Breast cancer dataset is juxtaposed with recent studies employing Bayesian belief networks (BBN) on the same dataset. The proposed WBBN and FWBBN models, constructed using the Breast cancer dataset, demonstrate superior accuracy compared to recent works by [35] with an accuracy of 97.13%, [38] with 96.49%,[41] with 87%,[8] with 97.1% [42].

The WBBN and FWBBN's accuracy on the Heart disease dataset is compared with recent work done using BBN on the exact datasets. Here the proposed model WBBN and FWBBN developed using the Heart Disease dataset achieves higher accuracy when compared with recent work developed by [36] with an accuracy of 84%. Similarly, the model, WBBN, and FWBBN on the PIDD are compared with recent work done using BBN on the exact dataset. Here the models WBBN and FWBBN are developed using the PIDD, achieves higher accuracy when compared with recent work developed by [37] with an accuracy of 92.2% and [40] with an accuracy of 82.48%. At last, the overall comparison of the proposed models, WBBN and FWBBN, with existing Predictive models and BBN model shows that the proposed models outperform in terms of accuracy achieved.

7. CONCLUSIONS AND FUTURE SCOPE

In conclusion, the predictive model demonstrates satisfactory performance across various clinical datasets sourced from the UCI machine learning repository, affirming its effectiveness in real-world clinical applications. The model, characterized by its high accuracy, emerges as a versatile network applicable to diverse clinical scenarios. The extensive investigation of Bayesian Networks presented in this study contributes novel insights beneficial to the medical community.

The initial model, WBBN, reveals through experimental results that the incorporation of weighted concepts significantly enhances accuracy in clinical contexts, surpassing other available predictive models. In the subsequent model, FWBBN, the accuracy further improves, outperforming both WBBN and other Bayesian models, particularly with the integration of fuzzy weighted concepts. A comprehensive comparative analysis against existing predictive models and other Bayesian models demonstrates the superior

performance of the proposed WBBN and FWBBN models.

The developed clinical decision support systems, WBBN and FWBBN, are deemed future-ready. However, there is potential for further exploration, as these models could extend beyond clinical datasets to benefit other sectors. The network's applicability might be expanded to encompass various diseases, enabling the prediction of a patient's survival probability based on the conditions they are afflicted with.

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