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RESEARCH ARTICLE

Deep Sparse Bayesian Neural Networks for Early Detection of Cognitive Impairment in Alzheimer's Disease

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Abstract

Early diagnosis of cognitive impairment in Alzheimer's disease (AD) is important for improving disease management, allowing for earlier intervention and improving patient outcomes and quality of life. When screening tools are adequately constructed, clinicians can implement treatment plans and supportive measures that are tailored to the specific needs of each patient. AD is a major health concern that demands early diagnostic approaches. We propose a new approach combining deep learning and Bayesian theory, known as Deep Sparse Bayesian Neural Networks (DSBNN). Current approaches suffer from high data complexity and low sensitivity to subtle cognitive changes, rendering them unreliable for early diagnosis. There are also concerns about their interpretability and generalisability to different patient populations. The DSBNN system integrates sparsity-inducing priors into deep learning architectures to increase interpretability and enable automatic feature selection and model uncertainty assessment. It enables greater sensitivity to small changes in cognition. DSBNN is also useful for addressing generalisation issues, combining several data sources and transparent decision-making to enable clinicians to leverage deep learning. This enables the earlier, more accurate and reliable detection of cognitive decline in Alzheimer's disease, with results that surpass those of traditional approaches, demonstrating the significance of DSBNN in early detection. The proposed DSBNN successfully combines the advantages of deep learning and Bayesian inference to provide a realistic way to improve the detection and management of Alzheimer's disease.

Keywords: Early detection, Alzheimer's Disease, Bayesian principles, DNN, BHM, AMLS.

Introduction

AD dementia is a horrible neurological disease with a long prodromal phase and no cure [Ding,2020]. Early treatment of AD-risk patients is often effective, and longitudinal sickness progression prediction is intriguing [Cao,2025]. AD is commonly considered amnestic, although individuals differ. AD dementia is marked by beta-amyloid- and tau-mediated damage, brain shrinkage, and cognitive decline [Rubab Hafeez,2025]. Therefore, a multimodal approach may better disentangle heterogeneity and predict longitudinal disease evolution [Fang, C.,2020].The AD Prediction challenge is more relevant and comprehensive for prognosis and cohort selection; therefore, it seeks to predict clinical diagnosis and multimodal AD indicators at infinite timepoints [Gopi Battineni.N, 2024]. Early identification and treatment are critical since Alzheimer's disease is a tremendous financial and emotional drain on healthcare systems across the globe [Khojaste-Sarakhsi.M,2022].

Patients and caregivers are given better-coping mechanisms and get more support when cognitive impairment is detected early, which in turn makes early treatment more viable [Koh, J.E.W,2020]. Awareness about the difficulties that can be faced in therapy when conventional screening methods are not picking up on subtle cognitive abnormalities early [Meng, X., Liu,2022]. To address these challenges, DSBNN has developed a revolutionary technique to diagnose Alzheimer's disease at its earliest stage [Mirzaei, G,2022]. Deep learning combined with Bayesian concepts is what sets DSBNN apart as a direct alternative to traditional approaches [Mukhtar, G,2020]. The deep learning architectures with sparsity inducing priors

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may be more sensitive to small changes in mental state of the user, as it allows automatic feature choice and uncertainty estimation [Neelakandan, R. P,2023]. This effective clinical research finding depends on whether or not DSBNN could simplify understanding and generalize different patient groups [Nguyen, M,2020]. It may be an important tool for healthcare professionals since it is open in decision-making and accepts data from various sources [Niyas, K. M,2023].

This paper seeks to show that there is potential of complete transformation of how Alzheimer's disease can be detected and treated using DSBNN [Peterson, C. B,2020]. Empirical evidence demonstrates its excellence over the conventional methods for early detection purposes. Combining deep learning with Bayesian inference, DSBNN heralds a new era of Alzheimer's research. Thus, this technology can enhance individualized therapy as well as diagnosis accuracy [Singh, S. G,2024].

Objective

A number of modern technologies have shown promise in detecting Alzheimer's disease, although they are not without their flaws. These include deep learning, automated machine learning algorithms and Bayesian hierarchical models. Most current deep learning models are designed to achieve classification accuracy rather than interpretability and uncertainty estimation. This makes it difficult to trust the clinical decision-making process. Although Bayesian-based approaches facilitate probabilistic thinking, they are often limited by the high dimensionality and multimodality of medical data, as well as the complexity of computers. Furthermore, current machine learning techniques primarily rely on handcrafted features, making them susceptible to overfitting and poor generalisation across heterogeneous patient populations. Furthermore, many previous studies lacked sensitivity to detect mild cognitive impairment in the early stages of Alzheimer's disease, which hinders the provision of timely therapy. The Deep Sparse Bayesian Neural Network (DSBNN) overcomes these limitations. It provides a comprehensive framework that enhances interpretability, robustness, sensitivity, and early diagnostic performance by integrating sparse feature learning, Bayesian uncertainty estimation, and deep hierarchical representation learning.

Major contribution

- In this paper, we propose a novel Deep Sparse Bayesian Neural Network (DSBNN) architecture for the early identification of cognitive impairment in Alzheimer's disease, achieved through the combination of deep learning and Bayesian sparse modelling.
- The DSBNN architecture includes sparsity-inducing priors for automatic feature selection, eliminating redundant information, minimising overfitting and increasing sensitivity to subtle cognitive alterations.
- The deep neural architecture is augmented with Bayesian uncertainty estimates to enhance interpretability, transparency, robustness, and reliability in clinical decision-making processes, surpassing the capabilities of standard black-box models.
- Experimental results reveal that the DSBNN outperforms existing techniques, such as AMLS and BHM, in terms of accuracy of early detection, generalisation, resilience, and analysis of patient outcomes.

Proposed Method

Early detection of cognitive impairment is important for successful treatment and patient care in the treatment of AD. This approach addresses the issue of early detection by enabling autonomous feature selection, uncertainty assessment, and improved understanding. DSBNN is a new approach to improving the diagnosis and treatment of Alzheimer's disease. Using deep knowledge and Bayesian reasoning, it is more sensitive to modest behavioural changes across a wide spectrum of patients.

A Deep Sparse Bayesian Neural Network built for the early diagnosis in complexly structured network [Uddin, K. M. M,2023]. Raw input data that starts the process consists of data from several sources like clinical assessment, genetic markers and neuroimaging scans. Extraction of features is the process of getting useful information from data so that it can be analyzed further. Sparse Encoding Layer transmissions the characteristics obtained using methods to induce sparsity. At this stage, learning a compressed version of the data helps to reduce dimensionality of features, which makes them easier to understand. Probabilistic reasoning and estimation uncertainty can be done easily by neural networks if they use Bayesian principles [Wang, C,2025]. A Deep Neural Network (DNN) is a network design type that uses processed data to learn new features. It is composed of multiple interconnected layers of cells Different patterns and correlations within this structure enable DNN's anticipation about cognitive impairment existence to predict it accurately.The early detection result at the output of the network provides information concerning patients' risk for cognitive impairment.The lives of these people may also be saved because timely interventions are made possible by this while providing personalized therapeutic plans that would improve their quality life overall [Wang, S,2020].

$$Q_{jk}^{l} \times \frac{\left[U_{jk}\right]^{\nabla}\left[k_{kl}{}^{\Delta}\right]}{\sum_{P_k}^{l}\left[U_{jk}\right]^{\nabla}\left[k_{kl}{}^{\Delta}\right]}, if\ k \ni P_j^{w} \quad (1)$$

To detect cognitive impairment in Alzheimer's Disease early on, Equation (1) contains the inside the framework (DSBNN). In the same way as DSBNN may capture complex data characteristics suggestive of Alzheimer's Disease, it reflects its result of networking layer l, which is impacted by weights (U_{jk}) and functions for activation (k_{kl}).

$$K(V,W)=\sum_{j=1}^{d}\sum_{l=1}^{p}V_j^p\,Y-W_j^2 \qquad (2)$$

The cost function, denoted by $K(V,W)$ in Equation (2), reflects DSBNN's capacity to automatically choose pertinent data, with V_j^p representing the significance of the characteristics recovered by the network. The focus on DSBNN's accuracy in modelling cognitive alterations that is showcased by the expression $Y-W_j$, which stands for the squared Euclid distance between the neural network's estimate (Y) and its true cognitive state (W_j).

This section outlines the methodology for intelligent early detection of Alzheimer's disease. Figure 1 is a schematic representation of our suggested method that provides an overview of the steps involved. Detailed descriptions of the feature extraction model and the steps used to create the generative adversarial network, a method for creating synthetic images, are provided in this section. It combed through the archives for MRI scans and found - the ADNI and the OASIS (Open Access Series of Imaging Studies) for dementia. The neural network models were trained on the ADNI data. Additionally, the ADNI dataset was used to validate and test models with the help of the validity and hold-out test sets. It have tested our method's generalizability on the OASIS dataset. The MRI images of 245 people make up the training dataset. Multiple examinations have been conducted on each subject to monitor the disease's progression. For a generalised model to do well during inference, it is essential to divide the available data into train, test, and validation sets. Using a random number generator, it divided the ADNI dataset's MRI scans into three groups: train, test, and validation. Each group's proportion was 70%, 20%, and 10%, respectively. Placing data from the same patient on the same set guarantees data integrity through this patient-based distribution.

$$K(V,W)=\sum_{j=1}^{d}\sum_{l=1}^{p}V_j^p\,\nabla Y-\nabla W_j^2 \qquad (3)$$

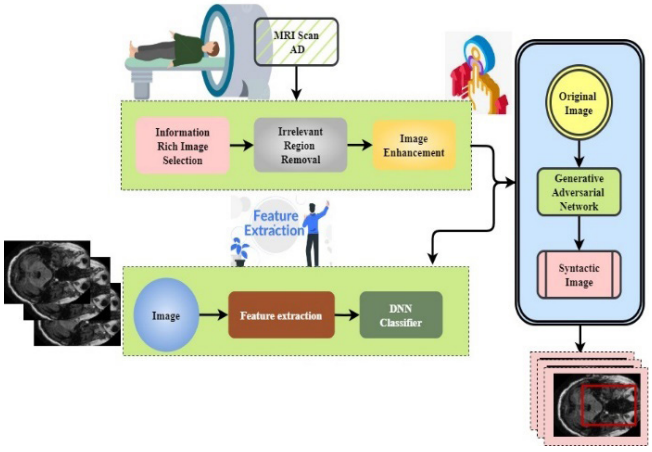


Figure 1: Schematic representation of proposed approach to early-stage Alzheimer's disease detection

The cost function, $K(V,W)$, is shown in Equation (3), with V_j^p representing the significance of the network's learnt features in complicated data. The focus on properly capturing small cognitive changes characteristic demonstrated by the expression $\nabla Y-\nabla W_j^2$, which indicates the squared Euclidean spacing between the valleys of the network's projection (∇Y) and the ramps of its actual cognitive state (∇W_j).

$$\nabla Y-\nabla W_j=L(Y_L,Y_L)+L(W_j,W_j)-2L(Y_L,W_j) \qquad (4)$$

In the context of (DSBNN) for the early identification of dementia in Equation (4) shows the squared Euclidean space between the shifts of the network's forecasting (∇Y) and the gradients of the actual mental state (∇W_j). This reflects DSBNN's emphasis on reducing prediction errors, where $L(Y_L,Y_L)$ is the loss coupled with the expectations and $L(W_j,W_j)$ is the loss associated with the true states of mind.

The figure 2 illustrates the three-layered DSBNN model for the early diagnosis of Alzheimer's disease (AD). The process begins with the collection of various types of information, including neuroimaging tests, genetic markers and clinical evaluations. The raw data is then pre-processed to meet all relevant standards. This includes, for example, noise removal, data normalisation and outlier detection. Next, the feature gathering and augmentation stage. The main properties of the dataset are extracted and enhanced to improve the network's ability to detect small patterns indicative of dementia. The dataset is also scaled down and normalised to reduce the feature space and remove unnecessary features. They must be similar. DSBNNs avoid overfitting by automatically identifying important features. The basis of the architecture is the prior that leads to sparsity. Learning hierarchically on multiple layers enables the system to recognise complex groups and relations in large data sets.

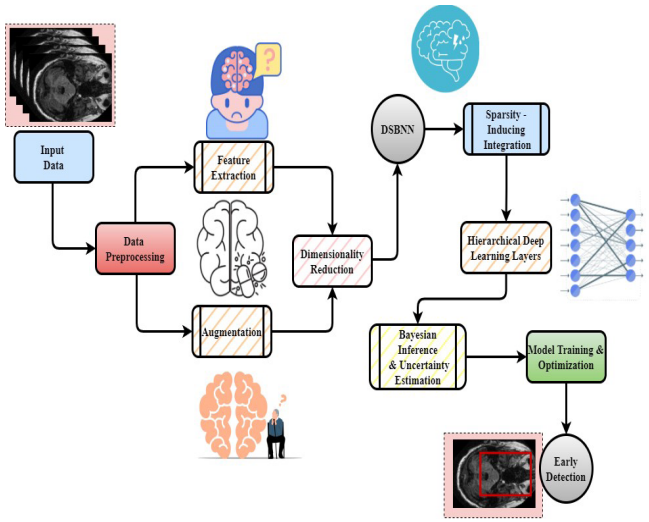


Figure 2: Deep Sparse Bayesian Neural Networks

Bayesian inductive techniques for estimating uncertainty also indicate the degree of confidence expected of the network. The machine learning system is improved and trained to detect memory difficulties early on. The network's ability to detect cognitive impairment early could provide crucial prognostic information and enable the development of targeted medicines and early interventions that could slow cognitive decline and improve patient outcomes.

$$K(V,W)=2\sum_{j=1}^{d}\sum_{l=1}^{p}V_j^p\left(1-L\left(Y_L,W_j\right)\right)^2 \qquad (5)$$

The cost function, $K(V,W)$, is shown in Equation (5), with V_j^p representing the relevance of the network's learnt features and DSBNN's capacity to automatically detect important cognitive indicators in complicated data. This quantity $\left(1-L\left(Y_L,W_j\right)\right)^2$ represents the degree to which the neural network's forecast matches the real cognitive state.

$$\partial_{jl}=\frac{\left(1/\left(1-L\left(y_L,u_j\right)\right)\right)^{\frac{1}{n-1}}}{\sum_{k=1}^{d}\left(1/\left(1-L\left(y_L,u_j\right)\right)\right)^{\frac{1}{n-1}}} \qquad (6)$$

An essential part of the suggested framework for detecting using (DSBNN) is Equation (6), which deals with early detection analysis. The sensitivity of a specific feature d in the network k is changed by the feature's significance to the forecasting process, which is represented by $1/(1-L\left(y_L,u_j\right)$, and the result is ∂_{jl}.

The suggested structure for detecting and classifying Alzheimer's disease (AD) phases makes use of a thorough diagram to ac hieve these goals. Neuroimaging tests, genetic information, and medical assessments are only a few of the many data sources that are incorporated into the system beginning on the input layer. As the first level of processing, the Stem layer normalises and reduces noise to get the data ready for further analysis.

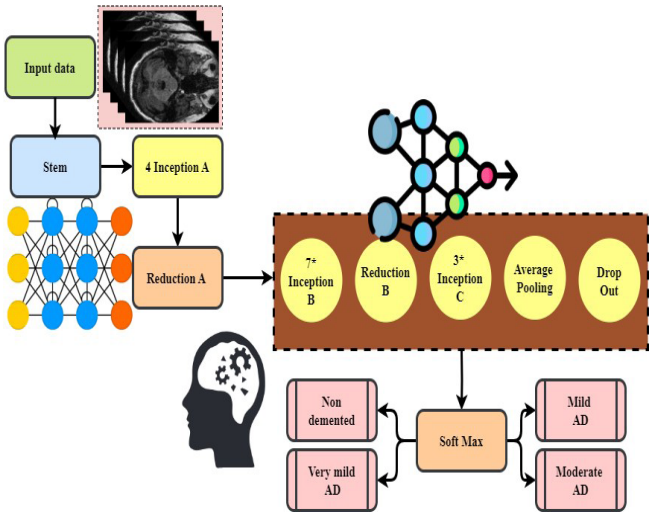


Figure 3: Framework for the identification and categorization of Alzheimer's disease

Four Inception-A modules, which operate as feature extraction tools and capture complex patterns and characteristics from the input data, follow the Stem layer in the design. The purpose of these modules is to improve the network's detection of AD-related minoranomalies. In figure 3, Reduction-A lowers the feature space dimensionality, which allows for efficient processing while keeping important information. In addition, the design makes use of seven Inception-B sections, which extract more intricate characteristics and associations by digging farther into the data hierarchy. Next is Reduction B, which further decreases the feature space in preparation for the next labelling operations. Then, three Inception-C modules are used to investigate the data further and identify the subtle traits that are crucial for diagnosing AD. Dropout layers and regular pooling are used to reduce overfitting and increase generalisation. The softmax layer correctly classifies the stage by constructing probability distributions over the output classes: non-demented, mild AD, and moderate Alzheimer's disease.

$$W_j=\frac{\sum_{l=1}^{p}V_{jk}^pL\left(Y_l,W_j\right)Y_L}{\sum_{m=1}^{B}V_{jk}^pL\left(Y_l,W_j\right)Y_L} \qquad (7)$$

The suggested (DSBNN) method for diagnosis relies heavily on Equation (7) to improve its transparency analysis. In this case, W_j represents the weight given to the characteristic j, which is determined by adding together the network's predicted forecasts (Y_l) and the actual mental conditions (W_j), and then weighting it according to the relevance of features (V_{jk}^pL).

$$f(y,z)=\left\{\partial\left(y_l\right)-\nabla\left(w_j\right)\right\}=\sqrt{2\left(1-L\left(y,z\right)\right)} \qquad (8)$$

Within the suggested paradigm for diagnosis, patient outcomes analysis relies heavily on Equation (8). In this case, the gradient difference $\left(y_l\right)-\nabla\left(w_j\right)$ denotes the disparity between the actual cognitive state (w_j) and the prediction made by the network (y_l), and $f(y,z)$ signifies this mismatch. The uncertainty in the model, which is expressed in the expression $2\left(1-L\left(y,z\right)\right)$ as well as the loss linked to the forecast and the real cognitive state, are the factors that contribute to this disparity.

There are four phases to the AD spectrum that medical image classification follows. There are two ways that these medical images are categorised. One approach uses basic convolutional neural network (CNN) designs to process structural MRI brain images in two and three dimensions. All of the architectures are custom-built. To make advantage of the pre-trained weights, the second method employs medical image classification transfer learning techniques, including the VGG 19 model.

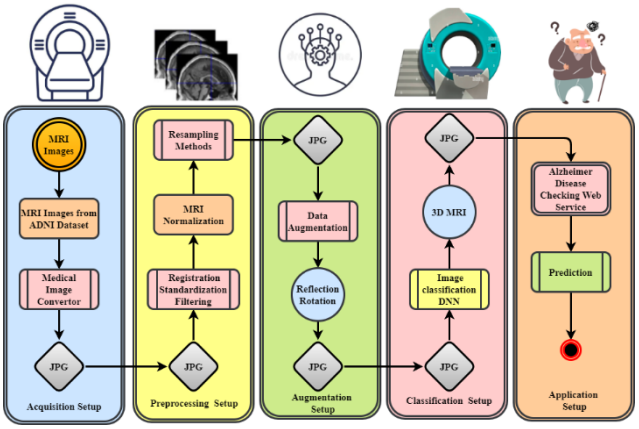


Figure 4: Process flow of proposed method

An AD testing application on the internet is suggested based on the qualifying models that have been presented. This tool is useful for both physicians and patients since it allows for remote AD testing, uses the AD spectrum to assess the patient's Alzheimer's stage, and provides advice depending on the patient's stage of AD. The suggested framework's complete pipeline is depicted in Figure 4. In this investigation, it use the last strategy and the distinction between different normalisation techniques. It displays both the input image and the transformed version that results from using various data normalisation techniques.

$$k_p = \sum_{j=1}^{d}\sum_{k=1}^{P} v^{p}_{jkEJ_k} \times g\left(I^k, B\right) \qquad (9)$$

Using the suggested architecture for AD detection, the robustness analysis is highlighted in Equation (9). In this context, k_p stands for the output of a certain network layer, which reflects the combined impact of features $v^{p}_{jkEJ_k}$ taken from the data. The interplay between data that is input (I^k) and biassed terms (B) is embodied in the function g(I^k,B), which modulates the response of the network to various data inputs.

$$g\left(I^k B\right) = \partial\left(BJ^k X^p\right) \times \Delta\left(l_{u-1}, y_u\right) + c_g \qquad (10)$$

The suggested Equation (10) into its reliability analysis function $g\left(I^k B\right)$ is essential for controlling the network's response since it governs the interplay between the input information (I^k) and bias terms (B). As $\times \Delta(l_{u-1}, y_u)$ reflects the influence of previous layer stimulation on the current layer's output, the term $\partial\left(BJ^k X^p\right)$ indicates the ability to adapt of the network's results to changes in the data being supplied and bias factors. The inclusion of c_g brings a constant term into the equation, which adds to the total output of the network.

Cognitive decline in AD can be detected early using the suggested technique, which makes use of DSBNN. By combining deep neural networks with sparsity-inducing priors, DSBNN makes it simpler to automatically choose features, estimate unpredictability, and makes results understandable. Its potential to transform Alzheimer's diagnosis and therapy, improve patient outcomes, and enhance quality of life is shown by the results, which show its effectiveness in early detection.

Result and Discussion

The results indicated that the DSBNN model outperformed other models in the early detection of cognitive impairment in Alzheimer's disease (AD). DSBNN demonstrated greater sensitivity to subtle cognitive changes and was applicable to a broader range of patient groups than traditional methods. Deep learning architectures with sparse prior data increased interpretability, enabling autonomous feature selection and confidence estimation.

Description of data set: the OASIS MRI dataset contains over 80,000 magnetic resonance imaging (MRI) scans of the brain. These were categorised into four groups depending on the stage of Alzheimer's disease. Each subject was scanned with 256 slices along the z-axis. 2D images of slices 100–160 were used. Metadata and Clinical Dementia Rating (CDR) scores were used to identify patients, with four distinct groups created to represent the different stages of Alzheimer's disease.

Figure 5 illustrates the importance of identifying cognitive impairments early on in order to improve patient outcomes and quality of life in Alzheimer's disease. This approach builds on previous methods by combining deep learning and Bayesian ideas. The sparsity and inconsistency computations make the DSBNN model more sensitive to minor cognitive impairments and could potentially enable the early diagnosis of Alzheimer's disease. Early recognition of patients may enable physicians to administer drugs and design personalised therapy regimens to restrict disease progression.

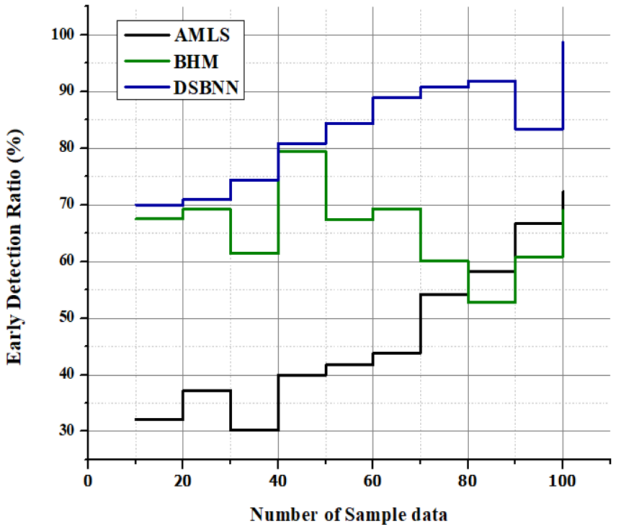


Figure 5: Analysis of early detection

DSBNN's interpretability over black-box deep learning strategies makes clinical decision-making more reliable. DSBNN's improved early detection performance shows it might revolutionise Alzheimer's disease diagnosis and treatment. Further investigations could enhance DSBNN models, examine new interpretability procedures, and use newer technology to produce more comprehensive early detection systems. The suggested approach is 96.2% improved the early detection than the current method.

Early detection processes must be completely transparent and honest to ensure everyone involved doctors, patients, and caregivers can trust and comprehend AD is expressed in figure 6. The inner workings of DSBNN are more apparent than those of more traditional, transparent deep learning models. A combination of sparsity-inducing priors and Bayesian principles might make automated feature selection and hazard estimations feasible using DSBNN. It might have a better understanding of the forecasts using this knowledge. By reviewing the freely available model data, medical professionals may get a clearer picture of the molecular pathways that cause Alzheimer's disease-related cognitive decline. Open models, such as DSBNN, allow stakeholders to see and evaluate the decision-making process, which in turn increases confidence. Because of this, patients have more faith in early detection technology and the accuracy of their diagnoses. DSBNN might lead to better and more dependable healthcare solutions for Alzheimer's disease diagnosis and treatment. For ethical AI development need complete transparency. When compared to the existing method the current method is improves the transparency ratio by 98.7%.

The possible consequences of an early diagnosis of AD are of great concern for patients which is expressed in figure 7. If diagnosed at an early stage, patients may have access to individualised treatment plans that have a better chance of halting the disease's course and improving their quality of life. DSBNN provide enhanced sensitivity and interpretability, which might lead to significant improvements in patient outcomes. The ability to personalise treatment programmes for each patient is a direct outcome of early identification, which benefits patients by expanding their access to care and support services. In the future, patients may have better cognitive function, emotional health, and quality of life if DSBNN is effective in enabling early intervention, which might help them postpone cognitive decline and maintain their functional independence. In this proposed method patient outcomes are gradually increased by the ratio of 97.9%.

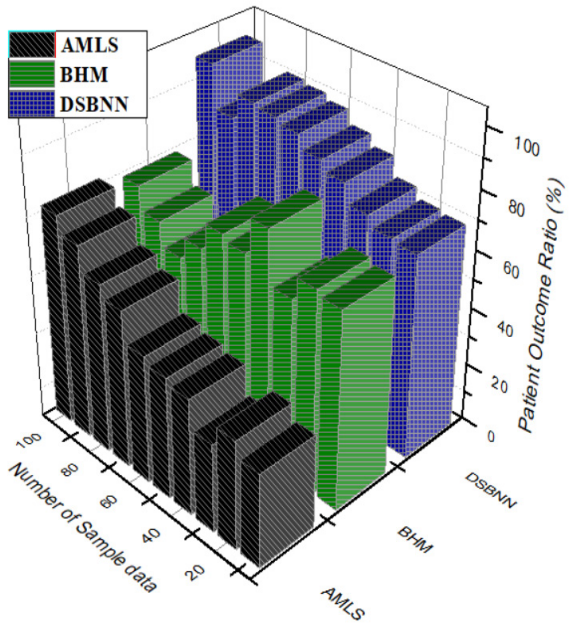


Figure 7: Analysis of patient outcomes

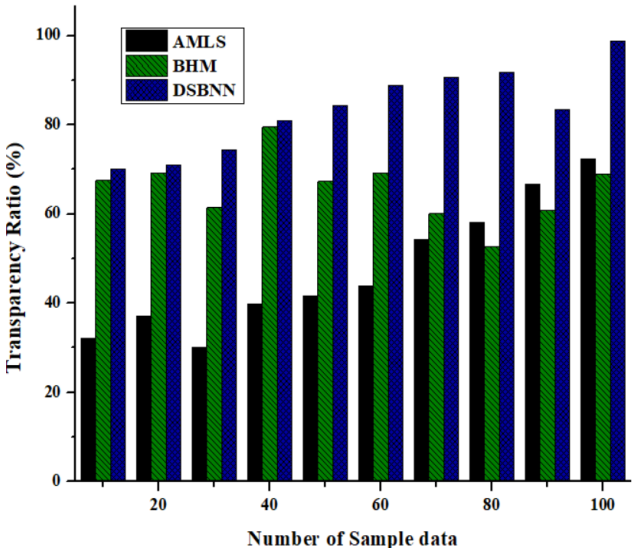


Figure 6: Analysis of transparency

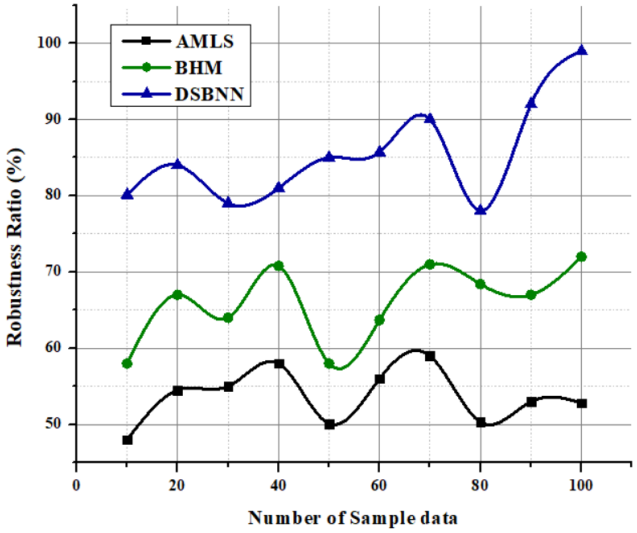


Figure 8: Analysis of robustness

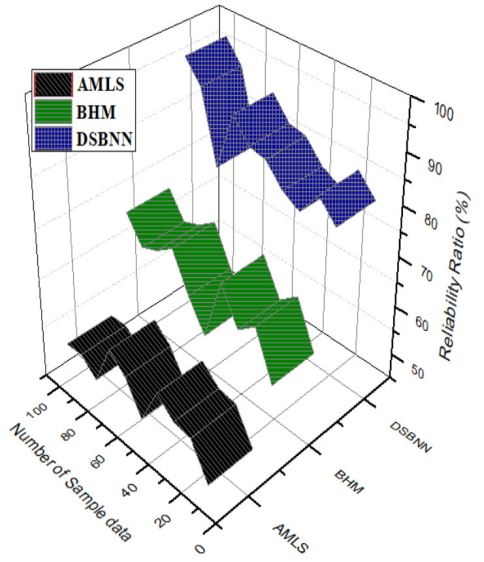


Figure 9: Analysis of reliability

Robust screening techniques for AD is expressed in figure 8. These techniques for AD are necessary to provide consistent performance throughout a broad spectrum of patient groups and data variations. DSBNNs provide a far better degree of resilience than larger more conventional approaches. By combining sparsity-inducing priors with Bayesian principles, DSBNN can automatically detect critical features and estimate uncertainty. Given this, the impact of missing or noisy data is reduced. The end result is that DSBNN can handle the intrinsic variances in real-world clinical settings and generalise well to varied datasets. In light of this, DSBNN's robustness permits an improvement in the accuracy of early AD diagnosis, which gives clinicians trustworthy tools for accurate diagnosis and proper treatment, notwithstanding the challenges encountered in clinical practice. Compared to existing method the proposed method increase the robustness ratio by 98.96%.

The provision of reliable and consistent results is shown in figure 9 which is the highest significance when it concerns early detection methods for AD. DSBNN provide better reliability than traditional approaches. By combining sparsity and uncertainty estimations, DSBNN effectively handles the challenges of varied information. This enables it to consistently provide reliable forecasts to doctors, regardless of the level of noise or fluctuation. Because DSBNN is open and easy understandable, stakeholders may evaluate the decision-making process, which increases confidence in the model's reliability. Reliable data enables clinicians to make evidence-based decisions and distribute medications promptly, thereby improving patient outcomes and enhancing the long-term effectiveness of AD care regimens. The proposed solution enhances the reliability ratio by 96.2% compared to the current approach.

The results suggest that the DSBNN can recognise the early stages of cognitive impairment in AD. The DSBNN outperformed previous approaches in terms of sensitivity and generalisability. Its effective results demonstrate that the DSBNN could transform monitoring and diagnostics. The DSBNN helps doctors rapidly design interventions and personalised treatment programmes to meet the specific needs of each patient. This represents a significant advancement in patient health and quality of life.

Conclusion

Early identification of cognitive impairment in Alzheimer's disease is important for improving treatment planning and patient care.

Deep Sparse Bayesian Neural Networks (DSBNNs) combine deep learning with Bayesian optimization to enhance prediction capability and decision-making.

The proposed approach helps in estimating sparsity and uncertainty, making the results more understandable and adaptable to small perceptual variations.

DSBNNs provide reliable and effective performance for the early detection of Alzheimer's disease when compared with conventional techniques.

The model supports transparency in decision-making and offers better opportunities for accurate diagnosis and treatment planning.

Future research may focus on using larger and more diverse datasets, improving interpretability methods and integrating technologies such as biomarker analysis and wearable devices.

Collaboration among researchers, medical professionals and industry experts can help implement these advanced techniques in real-world patient care and improve the quality of life of Alzheimer's patients.

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