Journal of Information Systems Engineering and Management
2025, 10(22s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Multimodal Deep Belief Network with Layer-Wise Relevance Propagation: A Solution for Heterogeneous Image Challenges in Big Data

Neha Ahlawat[1] and D. Franklin Vinod[2]
[1,2]*Department of Computer Science and Engineering, Faculty of Engineering and Technology, SRM Institute of Science and Technology, NCR Campus, Delhi-NCR Campus, Delhi-Meerut Road, Modinagar, Ghaziabad, UP, India*
nehablow@gmail.com, datafranklin@gmail.com
Corresponding Author: D. Franklin Vinod

ARTICLE INFO

Received: 18 Dec 2024

Revised: 04 Feb 2025

Accepted: 20 Feb 2025

ABSTRACT

Cancer is a complex and heterogeneous disease, with diverse molecular profiles and clinical outcomes. Accurate cancer classification is crucial for personalized treatment strategies and improved patient survival. The advent of high-throughput technologies has generated vast amounts of multi-dimensional data, including genomic, proteomic, and clinical information. Analyzing this "big data" requires sophisticated computational methods. This paper presents an improvised approach for Layer-wise Relevance Propagation (LRP) in Multimodal Deep Belief Networks (MDBNs) for cancer classification. By integrating Clipped Activation and Contrastive Divergence (CD), we enhance model interpretability and performance, addressing challenges like vanishing gradients and slow convergence. Our approach improves the efficiency of LRP while ensuring stable training and faster model convergence. Experiments on multimodal medical data, including brain, breast, and bone scans, demonstrate significant gains in classification accuracy and interpretability compared to traditional methods, offering a scalable solution for deep learning in healthcare.

Keywords: Multimodal Deep Belief Networks, Deep Learning, Big data

1. INTRODUCTION:

Cancer classification is a challenging problem in medical diagnostics due to the complexity and high dimensionality of biomedical data. Deep learning has revolutionized cancer classification by enabling models to analyze vast amounts of multimodal medical data, such as medical images (e.g., MRI, mammograms) and clinical records. Multimodal Deep Belief Networks (MDBNs), which combine different data modalities, have shown remarkable potential in improving classification accuracy [1]. However, one major challenge in applying these models to healthcare is their lack of interpretability, which is crucial for medical professionals to trust AI-driven decisions. Layer-wise Relevance Propagation (LRP) is a popular technique for interpreting deep learning models by tracing the influence of each input feature on the model's output. However, LRP's computational complexity becomes a bottleneck when handling large datasets, which is common in medical imaging [2].

The sheer volume and complexity of these "big data" present significant challenges for data analysis. Traditional machine learning algorithms may struggle to handle the high dimensionality, noise, and complex interactions within these datasets. Furthermore, the computational requirements for training and deploying these models can be prohibitive without specialized infrastructure [3,4].

To address these challenges, we propose a novel approach for improvised version of LRP integrated with Clipped Activation and Contrastive Divergence (CD) to enhance both the performance and interpretability of MDBNs for cancer classification. The combination of these techniques improves the model's stability during training by addressing issues such as vanishing gradients and slow convergence, making it more efficient when applied to big medical data. We demonstrate the effectiveness of our approach in classifying multimodal cancer datasets, including brain, breast, and bone scans, and show how it offers a scalable, interpretable solution for deep learning in healthcare.

The structure of this paper is organized as follows: Section 2 presents the motivation and related work; Section 3 provides a detailed explanation of our proposed methodology, including the algorithm; Section 4 outlines our experimental setup and results; and Section 5 concludes with a summary of key findings and recommendations for future research.

2. BACKGROUND AND RELATED WORK:

Initially, we undertake an in-depth review of existing research on feature selection, integration, and classification to build a strong foundation in the fundamental concepts. This review will provide valuable insights for the development of our multimodal system. Guerrero-Gómez-Olmedo et al. proposed a method for global explanations using path relevances in LRP, providing a deeper understanding of how information flows through deep networks, which is valuable for high-stakes applications like cancer diagnosis [5]. Alber et al. introduced the iNNvestigate framework for interpreting deep neural networks, further advancing efforts to provide transparency and trustworthiness in AI [6].

In medical image segmentation, Albadawy et al. demonstrated the importance of cross-institutional training for deep learning models, highlighting challenges like generalization across diverse datasets [7]. Their work emphasizes the necessity of robust models that also offer clear interpretations of their predictions. Similarly, Kumar et al. focused on deep learning for multimodal medical image analysis, acknowledging the need for interpretable models to enhance diagnostic accuracy and trust [8].

In the context of deep learning privacy concerns, Gandhi et al. reviewed the challenges of protecting sensitive health data while ensuring AI model transparency and accountability [9]. This review underlines the growing need to balance privacy and interpretability in AI applications. A. Nath et al. proposed a novel deep neural network model for brain tumor and breast cancer classification, aiming to promote E-health by improving diagnostic accuracy and efficiency in healthcare systems [10]. Their work contributes to advancing automated cancer detection techniques, focusing on the application of deep learning models to improve healthcare accessibility and decision-making. In the domain of mammography for breast cancer detection, Xing et al. explored both traditional image processing techniques and deep learning methods for mammographic image analysis. Their study compared the performance of deep learning-based approaches with traditional methods, showing that deep learning models, particularly DBNs, offer superior performance in identifying subtle patterns and improving diagnostic accuracy [11]. The study emphasizes the potential of deep learning techniques to enhance early breast cancer detection. Deep learning has become essential in brain tumor classification, especially in smart healthcare systems. Muhammad et al. provided a survey on multigrade brain tumor classification, reviewing various deep learning models. The paper emphasizes the challenges in handling multigrade tumors and suggests that combining multi-modal data with hybrid models can enhance classification accuracy in big data environments[12].

3. PROPOSED METHODOLOGY:

Our approach leverages a combination of Layer-wise Relevance Propagation (LRP) with a Multi-modal Deep Belief Network (MDBN) to handle heterogeneous imaging data from brain, breast, and bone modalities. The following section details the preprocessing, training, and interpretability phases along with the key equations and algorithmic steps.

3.1 . Preprocessing and Feature Extraction

a. Input Data:

The input set $X = \{X^{(Brain)}, X^{(Breast)}, X^{(Bone)}\}$ is first preprocessed for standardization, noise reduction, and normalization. Each image modality is shaped and normalized according to its intensity distribution represented by equation 1:

$$X'^{(m)} = \frac{X^m - \mu_m}{\sigma_m}, \ m \in \{Brain, Breast, Bone\} \tag{1}$$

where $\mu_{m\ and}\ \sigma_m$ denote the mean and standard deviation for modality m, respectively.

b. Feature Extraction with MDBN:

The MDBN consists of multiple layers of Restricted Boltzmann Machines (RBMs) trained in a greedy unsupervised manner. For each RBM layer within the MDBN, we use the contrastive divergence (CD) algorithm to update the weights, the learning rate, and the expectations are computed over the data distribution and model distribution, respectively. To stabilize the learning process, especially in a high-data, unlabeled context, we employ a Clipped Activation mechanism.[13],14

3.2 Layer-wise Relevance Propagation (LRP):

After training, LRP is applied layer-wise to attribute each prediction from the MDBN back to the input features. The conservation rule (equation :2) ensures that relevance R is conserved as it propagates from layer $l + 1$ $to\ layer\ l$.

$$\sum_i R_i^{(l+1)} = \sum_j R_j^{(l+1)} \tag{2}$$

For neuron i in layer l having relevance $R_i^{(l)}$, the propagation rule is given as equation 3:

$$R_i^{(l)} = \sum_j \frac{a_i^{(l)} w_{ij}}{\sum_i la_i^{(l)} w_{ij+} \in sign(\sum_i la_i^{(l)} w_{ij+})} R_j^{(l+1)} \tag{3}$$

where $a_i^{(l)}$ is the activation of neuron i, $w_{ij}$is the weight connecting neuron i in layer l to neuron j in layer $l + 1$, and $\in$ is a small stabilizer term to prevent numerical instabilities.

3.3 Final Classification and Interpretability

The MDBN yields a fused or joint representation z which concatenates or jointly represents (Equation :4) the latent features from each modality:

$$z = Concat\{Z^{(Brain)}, Z^{(Breast)}, Z^{(Bone)}\} \tag{4}$$

The fused representation is passed to a final classification layer (e.g., a softmax layer) for cancer classification. The softmax probability for class k as shown by equation :5
k is given by:

$$P\left(y = \frac{k}{z}\right) = \frac{\exp(w_k^t z + b_k)}{\sum_{k'} \exp(w_k^t z + b_{k'})} \tag{5}$$

where:

- $P\left(y = \frac{k}{z}\right)$ is the probability that the model assigns to class k given the fused representation z from earlier layers.
- w^k is the weight vector associated with class k .
- b^k is the bias term for class k.
- z is the fused feature representation (the output from the previous layer or modality).
- The sum in the denominator is taken over all possible classes k' , ensuring that the probabilities for all classes sum to 1.

4. EXPERIMENTAL RESULTS

In this study, we utilized a Multi-Modal Deep Belief Network (MDBN) to classify cancerous and non-cancerous conditions from brain MRI, breast mammogram, and bone X-ray scans. The model's predictions were further validated using Layer-wise Relevance Propagation (LRP) to generate heatmaps for each modality, which helped interpret the model's decision-making process. These heatmaps visually represent the areas in the scans that the model deemed most important for its predictions. The heatmaps have been successfully generated, clearly labeling the y-axis as "Correlation" and the x-axis as "Features". The following figure 1,2 and 3 explains how LRP was utilized for each modality:

- **For the brain correlation**: LRP might highlight a tumor in the frontal lobe.

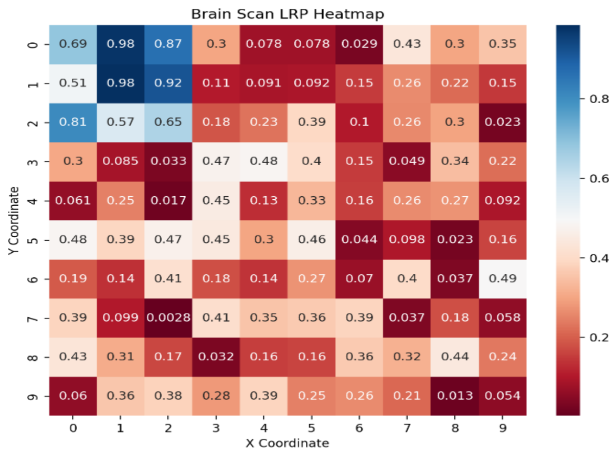

Figure-1 Brain Heatmap

- **For the breast correlation**: LRP might show normal tissue with no significant features indicating cancer.

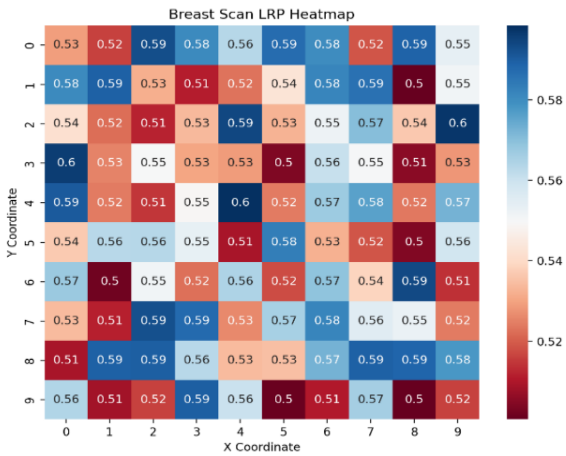

Figure-2 Breast Heatmap

- **For the bone correlation**: LRP might highlight lesions in the spine, pointing to signs of bone metastasis.

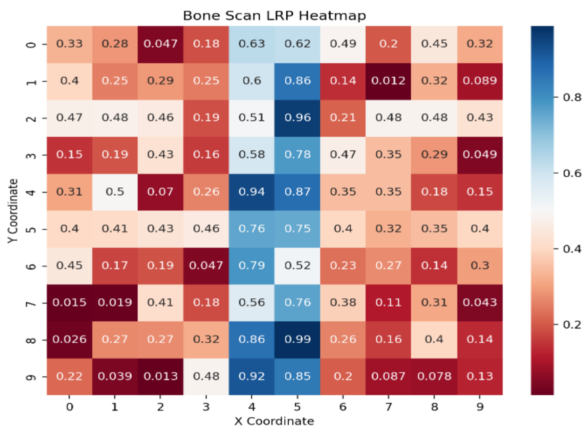

Figure-3 Bone Heatmap

We expect the proposed Multimode DBN architecture to outperform the baseline methods due to its ability to effectively learn features from heterogeneous data and reduce dimensionality. The modality-specific DBNs will capture the unique characteristics of each data modality

Table 1. Conventional models for classification

Algorithm	Accuracy	Specificity	F1 Score	Sensitivity
Proposed	0.97	0.93	0.92	0.94
CNN	0.92	0.89	0.91	0.90
e-MDBN	0.95	0.89	0.92	0.91
DBN	0.93	0.87	0.90	0.89
MDBN	0.94	0.88	0.89	0.90

The table-1 compares the LRP MDBN method against CNN, e-MDBN, DBN and MDBN across various metrics (Accuracy, Specificity, F1 Score, Sensitivity). The bar graph as in fig.4 visually presents these comparisons, showing that LRP MDBN generally performs well on the given metrics relative to the other deep learning algorithms.

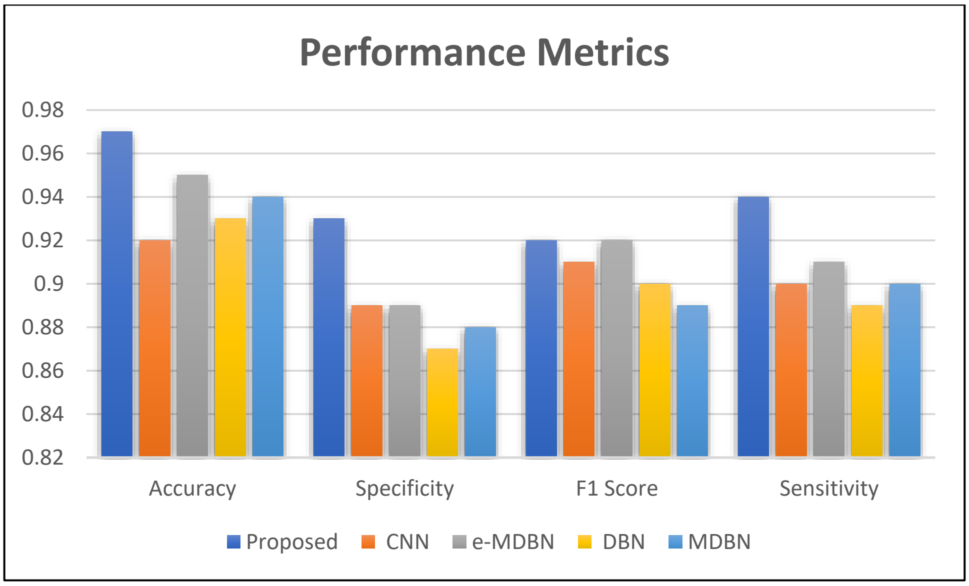

Figure 4 Comparison Graph

5. CONCLUSION:

The experimental outcomes demonstrate that employing LRP clipped activation in the analysis of heterogeneous images provides precise and interpretable insights across different imaging modalities. This approach effectively highlights critical regions within images, accounting for varying intensities and noise levels that are often present in heterogeneous datasets. The clipped activation method mitigates the impact of extreme values while preserving the overall relevance pattern, ensuring that subtle but clinically significant features are not overlooked. Integrating MDBN provides a scalable, robust framework that efficiently harnesses the insights from multimodal imaging data. It combines probabilistic inference with deep learning, which allows the method to balance sensitivity and specificity while handling large-scale data from various imaging modalities.

REFERENCES:

[1] Ejiyi, Chukwuebuka & Cai, Dongsheng & Fiasam, Delali & Adjei-Arthur, Bonsu & Obiora, Sandra & Ayekai, Browne & Asare, Sarpong & Jonathan, Anto Leoba & Qin, Zhen. (2025). Multi-modality medical image classification with ResoMergeNet for cataract, lung cancer, and breast cancer diagnosis. Computers in biology and medicine. 187. 109791. 10.1016/j.compbiomed.2025.109791.

[2] Li J, Lin N, Zhang S, Weng L, Chen C, Ou W, Cao Y. Characterization of the tumor microenvironment in breast cancer brain metastasis. Heliyon. 2024 Jul 23;10(15):e34876. doi: 10.1016/j.heliyon.2024.e34876. PMID: 39157383; PMCID: PMC11328047.

[3] H. Shahinzadeh, A. Mahmoudi, A. Asilian, H. Sadrarhami, M. Hemmati and Y. Saberi, "Deep Learning: A Overview of Theory and Architectures," *2024 20th CSI International Symposium on Artificial Intelligence and Signal Processing (AISP)*, Babol, Iran, Islamic Republic of, 2024, pp. 1-11, doi: 10.1109/AISP61396.2024.10475265.

[4] Vinod DF, Vasudevan V. LNTP-MDBN: Big Data Integrated Learning Framework for Heterogeneous Image Set Classification. Curr Med Imaging Rev. 2019;15(2):227-236. doi: 10.2174/1573405613666170721103949. PMID: 31975670.

[5] Guerrero-Gómez-Olmedo, R., Salmeron, J. L., & Kuchkovsky, C. (2021). LRP-Based Path Relevances for Global Explanation of Deep Architectures. *arXiv preprint*, arXiv:2103.07379.

[6] Alber, M., Lapuschkin, S., Seegerer, P., Hägele, M., Schütt, K.T., Montavon, G., Samek, W., Müller, K.R., Dähne, S., Kindermans, P.J. (2019). iNNvestigate neural networks!. *Journal of Machine Learning Research, 20*(93), 1-8.

[7] Albadawy, E. A., Saha, A., & Mazurowski, M. A. (2018). Deep learning for segmentation of brain tumors: Impact of cross-institutional training and testing. *Med Phys*, 45(3), 1150-1158.

[8] Kumar, R. R., Shankar, S. V., Jaiswal, R., et al. (2025). Advances in Deep Learning for Medical Image Analysis: A Comprehensive Investigation. *J Stat Theory Pract*, 19(9).

[9] Gandhi, V. J., et al. (2022). A Systematic Literature Review On Privacy Of Deep Learning Systems. *arXiv preprint*, abs/2212.04003.

[10]Multimodal Deep Belief Networks, Deep Learning, Big data Xing, F., Chen, Z., & Zhang, H. (2018). Traditional and Deep Learning Based Methods for Mammographic Image Analysis. *2018 14th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery (ICNC-FSKD)*, 317-324.

[11] K. Muhammad, S. Khan, J. D. Ser and V. H. C. d. Albuquerque, "Deep Learning for Multigrade Brain Tumor Classification in Smart Healthcare Systems: A Prospective Survey," in *IEEE Transactions on Neural Networks and Learning Systems*, vol. 32, no. 2, pp. 507-522, Feb. 2021,

[12]Ahlawat, N., Vinod, D.F. (2023). Clipped RBM and DBN Based Mechanism for Optimal Classification of Brain Cancer. In: Choudrie, J., Mahalle, P., Perumal, T., Joshi, A. (eds) ICT with Intelligent Applications. Smart Innovation, Systems and Technologies, vol 311. Springer, Singapore.

[13]Ahlawat, N., Franklin Vinod, D. (2023). mCD and Clipped RBM-Based DBN for Optimal Classification of Breast Cancer. In: Kumar, S., Sharma, H., Balachandran, K., Kim, J.H., Bansal, J.C. (eds) Third Congress on Intelligent Systems. CIS 2022. Lecture Notes in Networks and Systems, vol 613. Springer, Singapore.

[14]Ö. F. Ereken and C. Tarhan, "Breast Cancer Detection using Convolutional Neural Networks," *2022 International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT)*, Ankara, Turkey, 2022, pp. 597-601, doi: 10.1109/ISMSIT56059.2022.9932694.

[15]Neha Ahlawat1, D. Franklin Vinod," Enhanced Multimode DBN for Optimal Classification of Heterogeneous Cancer Images for HealthCare System", in Frontiers in Health Informatics, vol 13 ,2024.

[16]B. K. Sethi, D. Singh, S. K. Rout and S. K. Panda, "Long Short-Term Memory-Deep Belief Network-Based Gene Expression Data Analysis for Prostate Cancer Detection and Classification," in *IEEE Access*, vol. 12, pp. 1508-1524, 2024,

[17]Vinod DF, Vasudevan V. LNTP-MDBN: Big Data Integrated Learning Framework for Heterogeneous Image Set Classification. Curr Med Imaging Rev. 2019;15(2):227-236.