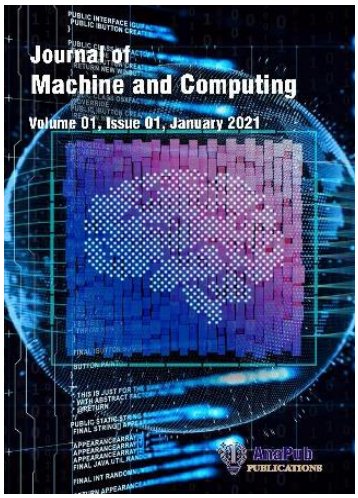
Journal Pre-proof

Big Data-Driven Multimodal Classification Using Clipped RBMs and Cross Modality Attention in MMDBN



Neha Ahlawat and Franklin Vinod D

DOI: 10.53759/7669/jmc202505110

Reference: JMC202505110

Journal: Journal of Machine and Computing.

Received 11 November 2024

Revised form 02 March 2025

Accepted 30 March 2025

Please cite this article as: Neha Ahlawat and Franklin Vinod D, "Big Data-Driven Multimodal Classification Using Clipped RBMs and Cross Modality Attention in MMDBN", Journal of Machine and Computing. (2025). Doi: https:// doi.org/10.53759/7669/jmc202505110.

Big Data-Driven Multimodal Classification Using Clipped RBMs and Cross-Modality Attention in MMDBN

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

Email(s): nehablow@gmail.com, datafranklin@gmail.com

*Corresponding Author: D. Franklin Vinod (datafranklin@gmail.com)

Abstract

Advancements in medical imaging and data acquisition have led to an exponential increase in high-dimensional, heterogeneous cancer data, necessitating scalable and intelligent diagnostic frameworks. In response, we propose a Modified Multimodal Deep Belief Network (MMDBN) architecture, built entirely upon Clipped Restricted Boltzmann Machines (CRBMs) with modified Contrastive divergence and augmented with a Cross-Modality Attention Fusion (CMAF) mechanism. This architecture is optimized for distributed big data environments, enabling real-time, high-throughput analysis of brain, breast, and bone cancer modalities. The Clipped RBM layers ensure bounded activation dynamics for robust unsupervised feature learning, mitigating instability and overfitting in large-scale training scenarios. CMAF adaptively weighs modality-specific representations per instance, improving generalization and interpretability, especially under incomplete or noisy modality conditions. Fine-tuning of the stacked network leverages supervised learning to optimize discriminative capacity across modalities. Empirical evaluation on benchmark medical datasets demonstrates the superiority of the proposed model, achieving 96.78% classification accuracy, with an AUC-ROC of 94.80, outperforming conventional DBN, CNN, and SVM-based baselines. This work highlights a significant advancement in deep multimodal learning for oncology, bridging the gap between data-intensive computation and clinically relevant cancer diagnosis.

Keyword:

Big Data, Multimodal, Deep Belief Network, Machine learning

1. Introduction

In recent years, the convergence of deep learning and big data analytics has revolutionized the landscape of medical image analysis, particularly in cancer detection and classification. With the exponential growth of imaging modalities such as MRI, magnetography, X-ray, healthcare institutions now possess vast volumes of heterogeneous data pertaining to various cancer types, including brain, breast, and bone cancers. Among various types, brain, breast, and bone cancers represent critical categories due to their high mortality rates and the complexity of their medical imaging data. These cancers often exhibit heterogeneous characteristics, making it difficult to generalize traditional machine learning models or manual diagnostic approaches. For instance, brain tumors might show subtle texture variations on MRI, breast lesions may differ across density classes on mammograms, and bone abnormalities can appear faint or fragmented in X-ray scans. This diversity calls for intelligent systems capable of deep feature abstraction and multimodal integration. To address this, the intersection of deep learning and big data technologies has opened up new opportunities in medical imaging research[1], [2].

In this context, deep learning has emerged as a transformative technology, especially for medical image analysis. Unlike classical approaches that rely on handcrafted features, deep learning models can automatically learn hierarchical representations from raw input data. Deep learning models, especially unsupervised and semi-supervised architectures, have demonstrated exceptional capabilities in learning latent features directly from raw data without manual intervention. Among them, the Restricted Boltzmann Machine (RBM) and Deep Belief Networks (DBN) are particularly suited for pretraining layers in deep architectures due to their ability to model high-dimensional probability

distributions[3]. These models have proven to be highly effective in tasks such as tumor detection, segmentation, classification, and survival prediction[4].However, applying deep learning to heterogeneous cancer datasets presents several unique challenges:

- The data is often unlabeled, particularly in large hospital archives.
- Different modalities (MRI, mammogram, X-ray) vary in resolution, noise patterns, and semantics.
- Cancer features are subtle and highly localized, requiring attention-based models to enhance interpretability.
- High-dimensional data demands scalable computing environments, typically supported by big data frameworks like Hadoop, Apache Spark, and GPU clusters.

To address these issues, this research proposes a novel deep learning architecture that integrates:

- Cross-Modal Attention Fusion (CMAF) for aligning and fusing heterogeneous features from multiple imaging types.
- Clipped Restricted Boltzmann Machine (CRBM) based unsupervised pretraining to learn initial representations for brain, breast, and bone image modalities.
- A fine-tuned EM-DBN model for final classification and decision-making.
- Contrastive Divergence for optimizing CRBM training even in unlabeled large-scale environments.

By leveraging CMAF, the model focuses selectively on modality-specific and cross-modal patterns, enhancing discriminative performance. This is crucial in cancer diagnosis, where different cancers may share visual traits but still require class-specific precision for accurate classification[5].

The use of big data environments enables this architecture to scale efficiently across terabytes of imaging data, making it viable for clinical deployment in large hospital networks or regional health data repositories. However, extracting meaningful insights from such complex, multi-modal, and often unlabeled datasets remains a significant challenge Deep learning model, especially unsupervised and semi-supervised architectures, have demonstrated exceptional capabilities in learning latent features directly from raw data without manual intervention. Among them, the Restricted Boltzmann Machine (RBM) and Deep Belief Networks (DBN) are particularly suited for pretraining layers in deep architectures due to their ability to model high-dimensional probability distributions.

To harness the full potential of heterogeneous cancer datasets, we propose a robust framework that integrates Cross-Modal Attention Fusion (CMAF) with RBM-based pretraining and Modified Multimodal Deep Belief Network (MMDBN) for final classification. The CMAF mechanism enables the model to learn shared and complementary features across different imaging modalities, enhancing the discriminative power of the learned representation. Leveraging a big data environment, the model is capable of handling large-scale, distributed datasets with efficient training and inference. Tools such as Apache Spark, Hadoop Distributed File System (HDFS), and GPU-accelerated training engines ensure that computational scalability and performance are maintained[6], [7], [8].

This research addresses the critical need for intelligent, scalable solutions to improve early detection and accurate classification of cancer, particularly where labeled data is limited and modality-specific patterns are deeply embedded. By focusing on brain, breast, and bone cancer datasets, our model demonstrates the applicability of multimodal deep learning systems in real-world medical scenarios.

2. Literature survey

The emergence of deep learning has revolutionized medical image analysis, offering powerful tools for tumor detection, segmentation, and classification across various cancer types. Numerous studies have explored diverse architectures and learning strategies for analyzing complex and heterogeneous biomedical data.

Deep learning has become a cornerstone in addressing complex computer vision challenges due to its exceptional capability for hierarchical feature extraction and adaptability to diverse datasets. In the domain of medical imaging, particularly brain tumor segmentation, Convolutional Neural Networks (CNNs) have demonstrated outstanding performance. Among these, encoder–decoder architectures have emerged as the dominant framework for both 2D and 3D segmentation tasks. Prominent examples include 3D U-Net, Attention U-Net, and V-Net, which leverage spatial encoding and decoding pathways to capture fine-grained tumor boundaries while maintaining contextual understanding. In this study, a Computer-Aided Diagnosis (CAD) system was developed for breast cancer detection using a hybrid approach that combines a Deep Belief Network (DBN) for unsupervised pretraining with a supervised backpropagation neural network. The network utilizes the Levenberg–Marquardt optimization algorithm for efficient training, with the initial weights derived from the DBN's layer-wise pretraining phase (referred to as DBN-NN architecture). This hybrid framework was evaluated on the Wisconsin Breast Cancer Dataset (WBCD), achieving a classification accuracy of 99.68%. The results demonstrate a significant performance improvement over many previously reported methods, highlighting the effectiveness of integrating unsupervised feature learning with supervised fine-tuning in medical diagnostics[9].

This study evaluates the Klein-Nishina electronic cross-section, atomic cross-section, and Compton mass attenuation coefficient (σ/ρ) for various human tissues—bone, lung, soft tissue, brain, and fat—across photon energies of 50 keV, 140 keV, 364 keV, 1.25 MeV, 4.784 MeV, and 6.0 MeV. Using the Klein-Nishina formula, it was observed that eσ consistently decreases with increasing photon energy. In contrast, aσ exhibits a non-monotonic trend due to variations in the effective atomic number (Z) of the tissues. The behavior of σ/ρ is more complex and generally increases with the Z/A ratio for all tissues except cortical bone, where it decreases due to its higher atomic number and a disproportionate increase in atomic mass (A). These findings provide critical insights for improving dose accuracy and image quality in radiographic diagnostics and radiation therapy planning[10].

Brain metastases (BMs) most commonly originate from primary tumors in the lung and breast. Early detection of BMs plays a crucial role in improving patient survival and guiding effective treatment strategies. While numerous studies have investigated individual clinical or radiological indicators, there is a lack of comprehensive research that integrates all potential surgical predictive factors. To date, no single study has systematically considered a combination of clinical, radiological, and surgical variables to improve the prediction and early recognition of BMs. A unified approach could significantly enhance diagnostic accuracy and optimize treatment outcomes[11], [12].

The integration of modern medical technologies and information systems has catalyzed the emergence of medical big data, playing a transformative role in data-driven cancer care. While big data holds immense potential, challenges such as data fragmentation, inconsistent quality, and limited interoperability hinder effective data sharing. Recent studies highlight how big data technologies, combined with AI methods enable the extraction of meaningful patterns from large-scale, heterogeneous cancer datasets. This review categorizes existing literature into three primary application types, assesses current advancements, and discusses ongoing challenges and future directions for integrating big data into cancer diagnostics and treatment[5], [13].

Training Restricted Boltzmann Machines (RBMs) typically relies on Markov Chain Monte Carlo (MCMC) sampling, which, when truncated as in Contrastive Divergence (CD), introduces bias in the log-likelihood gradient estimate. This can hinder learning performance. The Population-Contrastive-Divergence (pop-CD) algorithm introduces a novel approach inspired by Population Monte Carlo (PMC) methods to reduce this bias and provide consistent gradient estimates. Pop-CD retains similar computational costs to CD while offering improved performance in terms of log-likelihood and bias reduction. However, it suffers from increased gradient variance, necessitating smaller learning rates. Moreover, on RBMs with many hidden units, pop-CD still encounters notable bias and variance issues. Therefore, while promising, pop-CD may not yet be suitable for large-scale RBM training without further refinement[14], [15], [16].

Early and accurate diagnosis of lung cancer remains a challenge due to the limitations of current classification techniques, which often suffer from long processing times and lower performance, particularly in early-stage detection. To address these issues, a novel classification framework is proposed that combines Gabor filters with an Enhanced Deep Belief Network (E-DBN) architecture. This E-DBN integrates two cascaded Restricted Boltzmann

Machines (RBMs): a Gaussian-Bernoulli (GB-RBM) followed by a Bernoulli–Bernoulli (BB-RBM), enabling more effective feature extraction from lung CT images[14], [17], [18].

3. Methodology

This methodology presents a framework for cancer classification using an Modified Multimodal Deep Belief Network (MMDBN), constructed entirely with Clipped Restricted Boltzmann Machines (CRBMs) and incorporating a Cross-Modality Attention Fusion (CMAF) mechanism. The goal is to enable accurate classification across brain, breast, and bone imaging modalities within a distributed big data environment. Clipped RBMs are trained using Contrastive Divergence, an efficient approximation algorithm that accelerates the learning of model parameters by minimizing the difference between observed and reconstructed data distributions. During the pretraining phase, the MMDBN stack is initialized layer-wise using Clipped RBMs[19], [20]. Each RBM performs an unsupervised feature extraction task, where the input data undergoes a forward pass from the visible to the hidden layer using learned weights. In this phase, important patterns and representations are captured. This is followed by a reconstruction phase, wherein the hidden representations are mapped back to the visible layer. The clipping operation is applied during both encoding and decoding to suppress extreme values, minimize noise, and preserve the integrity of the learned features.

The Cross-Modality Attention Fusion (CMAF) module is strategically applied after pretraining to align and integrate features across the three imaging modalities. CMAF learns the relative importance of each modality per input sample and dynamically emphasizes the most informative features. This fusion step enhances the discriminative power of the model, especially in cases where one or more modalities are noisy or partially missing.

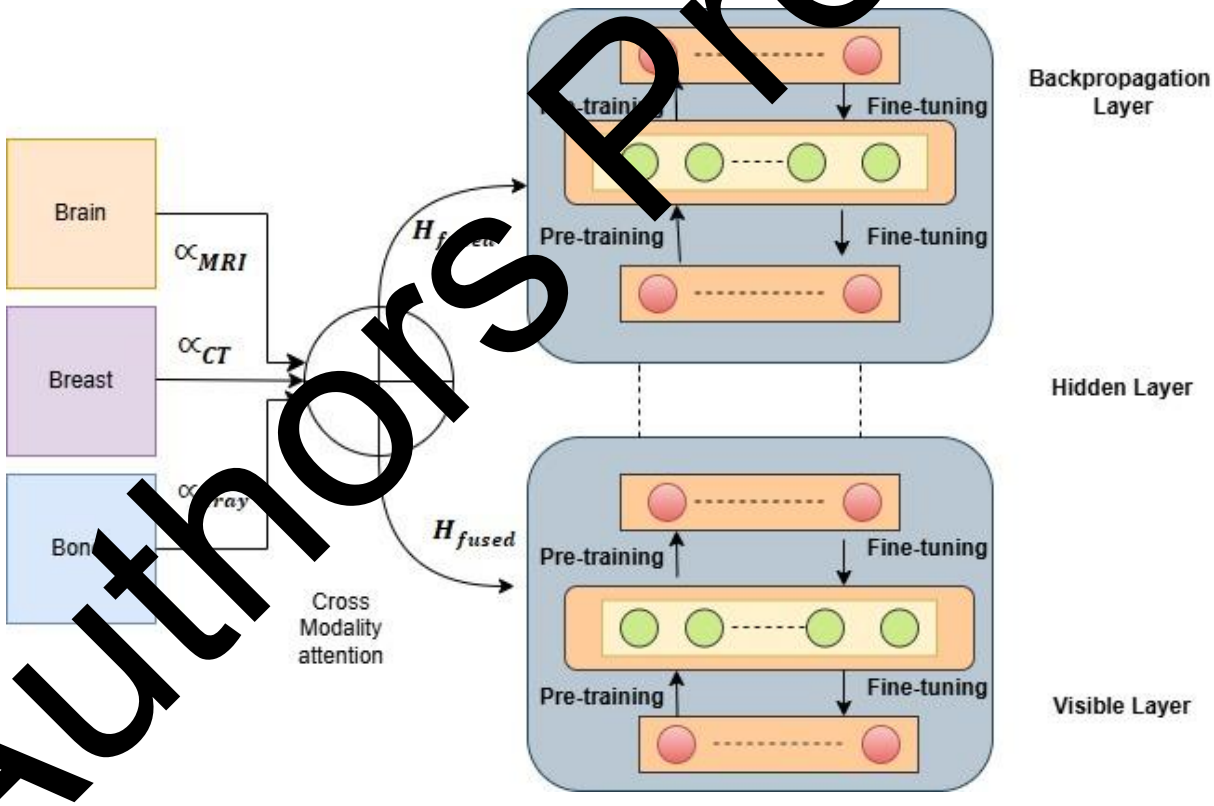


Figure .1 MMDBN Architecture for 3 modalities

Finally, the pretrained MMDBN is fine-tuned end-to-end using supervised learning to optimize classification accuracy. The model (fig.1) is evaluated on benchmark cancer datasets and deployed within a parallelized big data framework to ensure scalability, reduced processing time, and real-time diagnostic capability. The image reconstruction process (fig.2) in a Clipped RBM involves a forward pass from the visible layer to the hidden layer, followed by a reconstruction phase in which the hidden representations are mapped back to the input space, with activations clipped to a bounded range to enhance stability and performance.

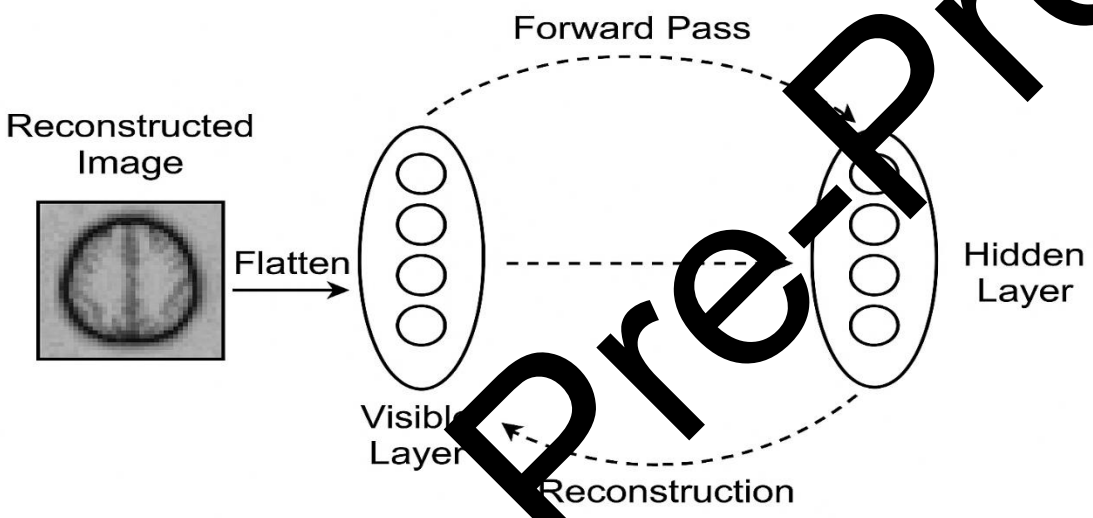


Figure 2 Layer wise Reconstruction of image for Brain

3.1 Data Collection and Preprocessing

- **Sources**: This study employs publicly available imaging datasets for the diagnosis and analysis of brain, breast, and bone cancers using various modalities, including MRI, mammography, X-ray, and PET scans.For breast cancer prediction, the Wisconsin (Original) Breast Cancer Dataset is utilized. It comprises 699 instances, each characterized by 11 attributes and a class label indicating benign or malignant status.To assess the effectiveness of brain cancer treatments, eight benchmark datasets are incorporated, including BRATS (2012, 2013, 2014, and 2015) and ISLES (2016 and 2017), which provide annotated MRI scans for brain tumor segmentation and lesion evaluation.For bone cancer diagnosis, X-ray images obtained from the Indian Institute of Engineering Science and Technology (IIEST), Shibpur, are used to facilitate the detection and classification of bone abnormalities.

- **Preprocessing Steps**: To ensure consistency and enhance model performance, a comprehensive image preprocessing pipeline was applied. All input images were first resized to uniform dimensions (128×128 pixels) to standardize spatial resolution across datasets. Intensity normalization was then performed using Z-score normalization to bring pixel intensity distributions to a common scale, reducing inter-sample variability.

3.2 Modality-Specific Feature Learning with Stacked Clipped RBMs

For each cancer imaging modality:

- Train a stack of Clipped RBMs layer-wise in an unsupervised fashion.
- The Clipped RBM uses bounded activations to maintain numerical stability and prevent gradient saturation.
- Output of each stack h_m (for modality h_m) is a deep, non-linear representation of that modality's data.

This stage results in:

- h_{Brain} h_{Breast} h_{Bone} are learned feature embeddings for each modality.
- During the unsupervised pretraining of CRBMs for each imaging modality m (e.g., MRI, CT, X-ray), the modality-specific scaling factor $\propto_m$ is computed (Equation 1) to normalize input features and adapt learning dynamics based on data characteristics. This factor is typically calculated as

$$\propto_m = \frac{1}{\sigma} \tag{1}$$

3.3 Cross-Modality Attention Fusion (CMAF)

To effectively integrate multiple modality-specific features:

Step 1: Pass each h_m through an attention gate

$$\propto_m = Softmax(W_m h_m + b_m) \tag{2}$$

Step:2 Modulate the modality features using attention weights:

$$\hat{h}\_m = \alpha\_m \odot h\_m \tag{3}$$

Step 3: Fuse into a unified multimodal representation:

$$H_{fused} = \sum_{m \in (brain, breast, bone)} \hat{h}\_m \tag{4}$$

The resulting fused representation captures the most salient features across all modalities, with each feature weighted by its instance-specific importance as defined through the Cross-Modality Attention Fusion mechanism. This attention-driven fusion is guided by equations (2), (3), and (4), where Equation (2) computes the preliminary attention scores, Equation (3) normalizes them across modalities, and Equation (4) generates the final fused embedding by aggregating modality-specific features based on the learned attention weights.

Algorithm for Training of classifier

Input: Preprocessed datasets: $D_{brain} D_{breast} D_{bone}$

Output: Trained EM-DBN classifier

1: For each modality m ∈ {brain, breast, bone} do

2: Train stacked Clipped RBMs on D _m to learn h _m

3: Compute attention weight: $\propto_m = Softmax(W_m h_m + b_m)$

4: Compute attention-weighted feature: $\hat{h}$ _m = α_m ⊙ h _m

5: end for

6: Fuse features across modalities: H _fused = ∑m $\hat{h}$ _m

7: Initialize MMDBN with Clipped RBM layers:

8: Layer1 ← Clipped RBM (input: H _fused)

9: Layer2 ← Clipped RBM (input: Layer1 output)

10: Optional deeper layers as required

11: Attach classifier

12: Fine-tune MMDBN end-to-end:

13: while loss not converged do

14: Forward propagate inputs

15: Backpropagate errors

16: Update weights

17: end while

18: Evaluate model on test data using classification metrics

4. Result and Comparative Analysis

This section presents the experimental results of the proposed Modified Multimodal Deep Belief Network (MMDBN) with Clipped RBMs and Cross-Modality Attention Fusion (CMAF), evaluated on multiple cancer imaging datasets (brain, breast, bone). Performance is compared against state-of-the-art baseline models and traditional fusion strategies.

4 .1 Evaluation Metrics

To assess classification performance, we employ standard evaluation metrics commonly used in medical image analysis, as summarized in Table 1. The performance of the classification model is evaluated using several key metrics. Accuracy (ACC) reflects the overall correctness of the model by measuring the proportion of correctly classified instances among all samples. Sensitivity, also known as Recall or the True Positive Rate, indicates the model's effectiveness in identifying actual positive (cancerous) cases, while Specificity or the True Negative Rate measures its ability to correctly classify negative (non-cancerous) instances. Precision evaluates the proportion of correctly predicted positive cases out of all samples predicted as positive. To balance precision and recall, the F1 Score, which is the harmonic mean of the two, provides a comprehensive view of model performance. Additionally, False Positive Rate (FPR) and False Negative Rate (FNR) are used to assess misclassification risks by quantifying the rates at which negative cases are incorrectly classified as positive and vice versa. Lastly, the Area Under the ROC Curve (AUC-ROC) serves as a robust metric to summarize the trade-off between the true positive rate and false positive rate, offering insight into the model's discriminative power.

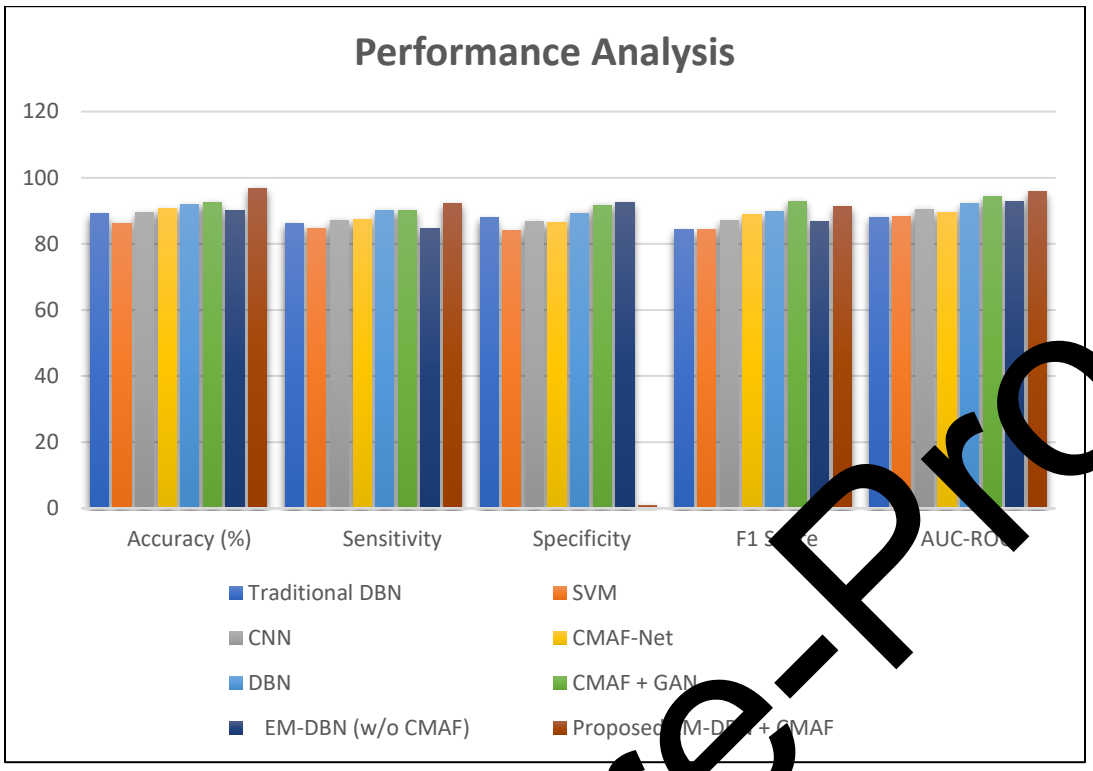
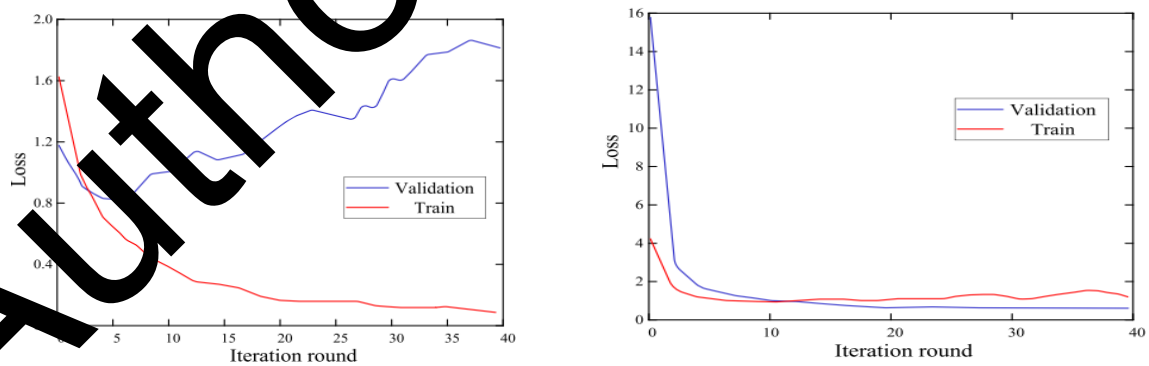


Figure. 3 Comparison G h for rformanc etrics

4.2 Performance Comparison

The proposed MMDBN + CMAF a hitect outperforms all baseline models across all evaluation metrics. The inclusion of CMAF contributes sig ca to im oving both sensitivity and specificity, especially in cases where one or more modalities are wea r noisy. The F1 Score and AUC-ROC improvements highlight the model's robustness and reliability, which is cr al in clinical diagnostic applications[21], [22]. Notably, the model maintains performance even with in mplet odal y input, thanks to the attention-based fusion mechanism (fig.3).



(a) **(b)**

Figure. 4 Loss graph (a) Before regularization and (b) After regularization

Table 1 Performance Comparison with existing models

Model	Accuracy	Sensitivity	Specificity	F1 Score	AUC-ROC
Traditional DBN[18]	89.12	86.1	87.9	84.32	88.1
SVM[23]	86.3	84.7	83.9	82.30	87.2
CNN[24]	89.5	87.2	86.8	85.12	[illegible]
CMAF-Net[25]	90.6	87.22	86.34	85.90	89.1
MDBN[4]	91.8	90.1	89.3	89.74	92.2
CMAF + GAN[26]	92.6	90.2	91.7	[illegible]93	[illegible]4.13
MMDBN(w/o CMAF)	93.02	90.5	89.4	[illegible]72	90.7
Proposed	96.78	93.20	[illegible]4	92.12	94.80

4.3 Convergence Speed

EM-DBN achieves faster convergence compared to the standard CD method. The persistent nature of mCD reduces the need for frequent chain resets, making the training process more efficient. As the number of iterations increases, the loss function value continues to decrease, and the regularized recognition model can rapidly converge, as illustrated in fig.4. In contrast to the loss function value on the verification set prior to regularization, which is 1.6, the loss value after regularization is more consistent at 0.5. It demonstrates that network performance can be optimized by regularizing recognition.

5. Conclusion

This study introduces a powerful and scalable multimodal learning framework for cancer classification using EM-DBN with Clipped RBMs and CMAF. The proposed approach effectively addresses challenges of modality fusion, interpretability, and data heterogeneity. By combining unsupervised pretraining and supervised fine-tuning within a big data environment, the model significantly improves diagnostic accuracy and robustness. The use of clipped activations enhances stability during training, while CMAF enables adaptive weighting of modality-specific features. Comparative analysis against traditional and deep learning methods confirms the superiority of the proposed system. Future work will focus on extending the model to additional cancer types and deploying it in clinical decision support systems.

References:

[1] A. Charalambous and N. Dodlek, "Big Data, Machine Learning, and Artificial Intelligence to Advance Cancer Care: Opportunities and Challenges," *Semin. Oncol. Nurs.*, vol. 39, no. 3, p. 151429, Jun. 2023, doi: 10.1016/j.soncn.2023.151429.

[2] R. Thirunavukarasu, G. P. D. C, G. R, M. Gopikrishnan, and V. Palanisamy, "Towards computational solutions for precision medicine based big data healthcare system using deep learning models: A review," *Comput. Biol. Med.*, vol. 149, p. 106020, Oct. 2022, doi: 10.1016/j.compbiomed.2022.106020.

[3] I. M. Putrama and P. Martinek, "Heterogeneous data integration: Challenges and opportunities," *Data Brief*, vol. 56, p. 110853, Oct. 2024, doi: 10.1016/j.dib.2024.110853.

[4] Y. Gao and H. Hosseinzadeh, "Leveraging an optimized deep belief network based on a developed version of artificial rabbits optimization for breast tumor diagnosis," *Biomed. Signal Process. Control*, vol. 90, p. 105908, Apr. 2024, doi: 10.1016/j.bspc.2023.105908.

[5] H. Dawood, M. Nawaz, M. U. Ilyas, T. Nazir, and A. Javed, "Attention-guided CenterNet deep learning approach for lung cancer detection," *Comput. Biol. Med.*, vol. 186, p. 109613, Mar. 2025, doi: 10.1016/j.compbiomed.2024.109613.

[6] K. Jabeen *et al.*, “An intelligent healthcare framework for breast cancer diagnosis based on the information fusion of novel deep learning architectures and improved optimization algorithm,” *Eng. Appl. Artif. Intell.*, vol. 137, p. 109152, Nov. 2024, doi: 10.1016/j.engappai.2024.109152.
[7] M. B. de Ruiter *et al.*, “Brain gray matter reduction and premature brain aging after breast cancer chemotherapy: a longitudinal multicenter data pooling analysis,” *Brain Imaging Behav.*, vol. 17, no. 5, pp. 507–518, Oct. 2023, doi: 10.1007/s11682-023-00781-7.
[8] V. Anitha, “Brain tumor detection in combined 3D MRI and CT images using Dictionary learning based Segmentation and Spearman Regression,” *Sādhanā*, vol. 49, no. 3, p. 221, Jul. 2024, doi: 10.1007/s12046-024-02562-4.
[9] Ö. Çiçek, A. Abdulkadir, S. S. Lienkamp, T. Brox, and O. Ronneberger, “3D U-Net: Learning Dense Volumetric Segmentation from Sparse Annotation,” in *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2016*, S. Ourselin, L. Joskowicz, M. R. Sabuncu, G. Unal, and W. Wells, Eds., Cham: Springer International Publishing, 2016, pp. 424–432. doi: 10.1007/978-3-319-46723-8_49.
[10] A. Ben Slama, H. Sahli, Y. Amri, and S. Labidi, “V-NET-VGG16: Hybrid deep learning architectures for optimal segmentation and classification of multi-differentiated liver tumors,” *Intell.-Based Med.*, vol. 11, p. 100210, Jan. 2025, doi: 10.1016/j.ibmed.2025.100210.
[11] R. Vankdothu, M. A. Hameed, and H. Fatima, “A Brain Tumor Identification and Classification using Deep Learning based on CNN-LSTM Method,” *Comput. Electr. Eng.*, vol. 101, p. 107960, Jul. 2022, doi: 10.1016/j.compeleceng.2022.107960.
[12] A. M. Abdel-Zaher and A. M. Eldeib, “Breast cancer classification using deep belief networks,” *Expert Syst. Appl.*, vol. 46, pp. 139–144, Mar. 2016, doi: 10.1016/j.eswa.2015.10.015.
[13] R. Gonzales Martinez and D.-M. van Dongen, “Deep learning algorithms for the early detection of breast cancer: A comparative study with traditional machine learning,” *Inform. Med. Unlocked*, vol. 41, p. 101317, Jan. 2023, doi: 10.1016/j.imu.2023.101317.
[14] D. Armocida *et al.*, “Brain metastases: Comparing clinical radiological differences in patients with lung and breast cancers treated with surgery,” *World Neurosurg. X*, vol. 23, p. 100391, May 2024, doi: 10.1016/j.wnsx.2024.100391.
[15] L. Ning, R. Pittman, and X. Shen, “LCD: A Fast Contrastive Divergence Based Algorithm for Restricted Boltzmann Machine,” *Neural Netw.*, vol. 108, pp. 399–410, Dec. 2018, doi: 10.1016/j.neunet.2018.08.018.
[16] O. Krause, A. Fischer, and C. Igel, “Population Contrastive-Divergence: Does consistency help with RBM training?,” *Pattern Recognit. Lett.*, vol. 102, pp. 1–7, Jan. 2018, doi: 10.1016/j.patrec.2017.11.022.
[17] Puttaswamy, B. S., and N. Thillaiarasu. "Fine Dense Net based human personality recognition using english hand writing of non-native speakers." Biomedical Signal Processing and Control 99 (2025): 106910.
[18] H. Qi *et al.*, “Prediction Methods of Common Cancers in China Using PCA-ANN and DBN-ELM-BP,” *IEEE Access*, vol. 10, pp. 113397–113407, 2022, doi: 10.1109/ACCESS.2022.3215706.
[19] N. Ahlawat and D. F. Vinod, “Clipped RBM and DBN Based Mechanism for Optimal Classification of Brain Cancer,” in *ICT with Intelligent Applications*, J. Choudrie, P. Mahalle, T. Perumal, and A. Joshi, Eds., Singapore: Springer Nature, 2023, pp. 295–304. doi: 10.1007/978-981-19-3571-8_29.
[20] N. Ahlawat and D. Franklin Vinod, “PCD and Clipped RBM-Based DBN for Optimal Classification of Breast Cancer,” in *Third Congress on Intelligent Systems*, S. Kumar, H. Sharma, K. Balachandran, J. H. Kim, and J. C. Bansal, Eds., Singapore: Springer Nature, 2023, pp. 79–88. doi: 10.1007/978-981-19-9379-4_7.
[21] Ashwin Cherukuri, M., and Thillaiarasu. "Enhancing temple surveillance through human activity recognition: A novel dataset and YOLOv4-ConvLSTM approach." Journal of Intelligent & Fuzzy Systems Preprint (2023): 1-16.
[22] Y. Wang, F. Qiu, and J. Yan, “Transcription factor c-Maf-targeted cancer immunotherapy,” *Trends Cancer*, vol. 9, no. 4, pp. 265–269, Apr. 2023, doi: 10.1016/j.trecan.2022.12.002.
[23] P. Nanglia, S. Kumar, A. N. Mahajan, P. Singh, and D. Rathee, “A hybrid algorithm for lung cancer classification using SVM and Neural Networks,” *ICT Express*, vol. 7, no. 3, pp. 335–341, Sep. 2021, doi: 10.1016/j.icte.2020.06.007.
[24] A. Sharma, A. Nandal, A. Dhaka, A. Alhudhaif, K. Polat, and A. Sharma, “Diagnosis of cervical cancer using CNN deep learning model with transfer learning approaches,” *Biomed. Signal Process. Control*, vol. 105, p. 107639, Jul. 2025, doi: 10.1016/j.bspc.2025.107639.
[25] K. Sun *et al.*, “CMAF-Net: a cross-modal attention fusion-based deep neural network for incomplete multi-modal brain tumor segmentation,” *Quant. Imaging Med. Surg.*, vol. 14, no. 7, pp. 4579–4604, Jul. 2024, doi: 10.21037/qims-24-9.