

Enhancing the Accuracy of Region of Interest Detection in Multi-Lesion Brain Tumors Using a Hybrid Deep Learning Network

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ABSTRACT

Precise detection of Regions Of Interest (ROIs) is essential in multilesion brain tumors for diagnosis and treatment planning. Most conventional methods, such as CNN and SVM, usually have a trade-off between precision and recall, misjudging tumor regions, and reducing diagnostic reliability. This paper proposes a Hybrid Deep Learning Network (HDLN) to address some limitations of conventional methods. The proposed HDLN combines CNNs for feature extraction with Long Short-Term Memory (LSTM) networks to integrate contextual information for more robust and accurate tumor region identification. This hybrid method combines the best of CNN and LSTM to improve accuracy in ROI detection. The proposed HDLN was thoroughly tested, indicating significant improvements over traditional methods, achieving a 0.15% increase in accuracy, a 0.12% increase in precision, and a 0.10% improvement in recall compared to CNN and SVM approaches. These advances indicate that the proposed HDLN can contribute to the field of ROI detection in medical images, offering clinicians a more credible and time-saving tool. Optimized parameters signified higher detection accuracy and reduced false positives and negatives. This paper describes the architecture, implementation, and thorough evaluation of the proposed HDLN, offering a prospective candidate to improve clinical workflow, diagnosis, and treatment planning for patients with brain tumors.

Keywords-Region Of Interest (ROI) detection; multi-lesion brain tumors; Hybrid Deep Learning Network (HDLN); Convolutional Neural Networks (CNN); Long Short-Term Memory (LSTM); medical imaging; tumor detection

I. INTRODUCTION

The precise detection of Regions Of Interest (ROIs) in multilesion brain tumors is still an active challenge in medical imaging. Accurate detection is instrumental in providing a confident diagnosis and efficient treatment planning [1]. Standard methods, including Convolutional Neural Networks (CNN) and Support Vector Machines (SVM), tend to suffer from precision and recall issues, offering region errors in tumor detection and poor diagnostic reliability. These challenges accentuate the urgency for more robust and accurate strategies to handle the complexity of multilesion detection in medical images [2].

Recent developments in deep learning have demonstrated the potential to overcome these limitations. Among them, a Hybrid Deep Learning Network (HDLN) can employ CNNs for feature extraction and LSTMs for contextual fusion, taking

advantage of both CNNs' and LSTMs' strengths by combining their complementarity, making it possible to have a more accurate and robust ROI detection in brain tumors. By combining spatial feature extraction with temporal contextual analysis, HDLNs considerably improve precision, recall, and accuracy compared to traditional approaches.

HDLN architectures are a major innovation in medical image analysis, providing more accurate and efficient multilesion brain tumor detection tools [3]. Beyond brain tumor detection, analogous hybrid models have shown great potential in detecting cardiovascular diseases, chest X-ray abnormalities, and retinal diseases in their early stages. When deployed in clinical workflows, these models can be beneficial in terms of improved diagnostic accuracy, fewer false positives and negatives, and overall improved outcomes for patients. However, the issues of heterogeneous integration of neural network modules, efficient training, and limited computational

overhead need to be resolved to realize the full potential of HDLNs in clinical applications. Using the strengths of both CNN and LSTM models, the proposed HDLN presents a novel solution to the long-standing problem of multilesion detection in brain tumors, opening the door to enhanced diagnostic tools in medical imaging.

A. Research Gaps

Although HDLNs offer some advances in the detection of ROIs in multilesion brain tumors, some limitations remain. One such limitation is the optimized integration of various neural network components within HDLN frameworks. Although the proposed architecture uses CNNs for feature extraction and LSTMs for integrating contextual information, intensive tuning is required to improve overall performance. Most methods require time-consuming training on multiple and complex medical images. Advanced training methods are required to improve robustness and reliability against real-world variability and complexity within medical imaging datasets [4]. Another issue is to reduce the computational burden of these models to make them more clinically applicable. As some advanced deep learning models have high computational demands that might limit their deployment to resource-constrained environments, further work should aim at more computationally efficient algorithms coupled with hardware acceleration techniques. Furthermore, extended validation is needed across various datasets to ensure the generalizability and robustness of HDLNs under field medical conditions. As current assessments may not reflect the variation inherent in clinical settings, further validation is required to uncover various shortcomings that may persist [5].

B. Related Works

Medical imaging has gone through many changes in recent years with the incorporation of machine learning and deep learning techniques, bringing about a complete change in the detection, segmentation, and classification of brain tumors. These innovations have been very useful to medical experts in improving patient results. Several methods and models have been proposed to increase accuracy and effectiveness in brain tumor analysis, each trying to solve this problem in different ways using different combinations of neural networks, optimization algorithms, and hybrid techniques to overcome the complexities. However, there are issues of model complexity, computational requirements, and generalizability, again pointing toward more research and development in this critical area.

In [6], a novel hybrid segmentation-based optimization-driven model was presented to classify brain tumors, combining the U-Net and CFPNet-M models with Tanimoto similarity and trained using Aquila spider monkey optimization. The hybrid segmentation model delineated and classified benign and malignant tumor samples with high efficiency, accuracy, sensitivity, and specificity, and low prediction error. However, the integration of various optimization techniques adds complexity in real-world implementation, making the process resource-consuming and less suitable for resource-limited environments.

In [7], a multimodal MRI fusion generative adversarial network was proposed for brain tumors, called BTMF-GAN, which focused mainly on improving the accuracy of ROI detection in fused images. The generator included a U-shaped nested structure with residual U-blocks combined with the MRF-ATFE module for more robust feature extraction. This approach balanced well between the details of the tissues and the structural contrasts in brain tumors, showing very promising qualitative and quantitative performance in both public and clinical datasets. In contrast, the introduction of new modules and loss functions increases the complexity of the model, which may affect the stability and speed of the model. Therefore, this method may not be suitable for clinical applications that require fast and simple solutions.

In [8], a deep parallel CNN combined AlexNet with VGGNet for the classification of brain tumor images. Single-point feature fusion and softmax-based classification achieved high binary and multiclassification performance. Although the model outperformed traditional SVM-based approaches, its dependence on pre-established architectures restricts its flexibility in processing new and varied datasets. Inconsistency in representing the patient population during the training process can decrease the generalizability of the model. In [9], an improved 3D fully CNN (V-Net) was proposed for liver tumor segmentation. This network included a pyramidal convolution block with deep multiresolution supervision and feature map fusion, achieving high segmentation precision and emphasizing hepatic blood vessel localization. Although the network achieved high Dice coefficient index values, its complicated structure prevents its extension for scalability to different tumor types or imaging modalities, except for considerable changes in architecture. In [10], a new method was proposed that involved Gabor filtering in conjunction with Gray Wolf Optimization (GWO), spatial fuzzy c-means clustering, and non-subsampled shearlet transform to classify brain tumors. In [11], a comprehensive review of brain tumor classification based on deep learning was presented. In [12], a vision transformer was embedded in ResNet to improve early brain tumor diagnosis. In [13], segmentation and classification of brain MRIs was conducted with the use of FCM-SVM.

C. Objectives

This study used an HDLN to improve efficiency, accuracy, and reliability in the detection of ROIs on multilesion brain tumors. The proposed approach was designed to eliminate the drawbacks of existing methods using the strengths of a CNN combined with an LSTM network. The objectives were:

- Design an HDLN that integrates CNNs and LSTMs for state-of-the-art ROI detection in multi-lesion brain tumors.
- Evaluate the performance of the proposed HDLN concerning accuracy, precision, and recall against traditional CNN and SVM methods.
- Integrate the CNN and LSTM parts of HDLN in an optimized way to improve the overall performance while minimizing computational overhead.
- Robustness: Employ the HDLN on multiple datasets of varied medical images, ensuring its clinical applicability.

D. Methodology

1) Phase 01: Brain Tumor Detection

The first stage is detecting the existence of brain tumors with a CNN for feature extraction. The main objective of this stage is to determine whether there is any tumor in the MRI.

a) Data Preprocessing

Brain MRI scans in the Karnataka Brain Tumor MRI Dataset (KBTMD) were normalized to a resolution of 256×256 pixels. Rotation, flipping, and scaling were employed for data augmentation to improve the model's generalizability. Noise reduction and contrast enhancement were performed to improve the clarity of tumor regions.

b) CNN Architecture

The CNN employed in this stage used convolutional layers to extract spatial feature maps of the MRI images, with subsequent pooling layers to reduce dimensionality. The output of the convolutional layers is fed into fully connected layers to infer tumor presence. Activation functions (ReLU) are applied along with dropout layers to increase performance and prevent overfitting. The last output layer classifies the MRI scans into either "Tumor" or "No Tumor" by applying a softmax function. Precision, recall, and classification accuracy are determined to evaluate detection performance.

2) Phase 02: Tumor Classification and Region of Interest (ROI) Detection

Once the tumor is identified, the next stage is to classify the type of tumor and precisely determine the ROI. This stage uses an HDLN method that amalgamates CNN and LSTM networks.

a) Feature Extraction using CNN

CNNs are used to extract high-level features from tumors found in Phase 01, which characterize the shape, texture, and boundary properties that are necessary for tumor classification.

b) Contextual Analysis with LSTM

The LSTM network processes temporal and spatial relationships between tumor regions. It takes advantage of the contextual connection between neighboring regions, improving multilesion performance.

c) Model Integration (CNN+LSTM)

The outputs of CNN and LSTM are combined to produce a final tumor type classification (e.g., Glioma, Meningioma, Pituitary). The model provides the class that is expected, along with each type's probability distribution.

d) Evaluation Metrics

The effectiveness of the merged model was determined by calculating accuracy, precision, recall, and F1-score. The designed HDLN demonstrated enhanced performance in comparison with conventional CNN or SVM approaches.

II. PROPOSED METHOD FOR ENHANCING ROI DETECTION IN MULTI-LESION BRAIN TUMORS

Figure 1 illustrates the workflow of the proposed technique to improve ROI detection in multi-lesion brain tumors. A comprehensive process was performed with several advanced techniques, subdivided into two main phases: Brain Tumor Detection (Phase 01) and Brain Tumor Classification and ROI (Phase 02) [14].

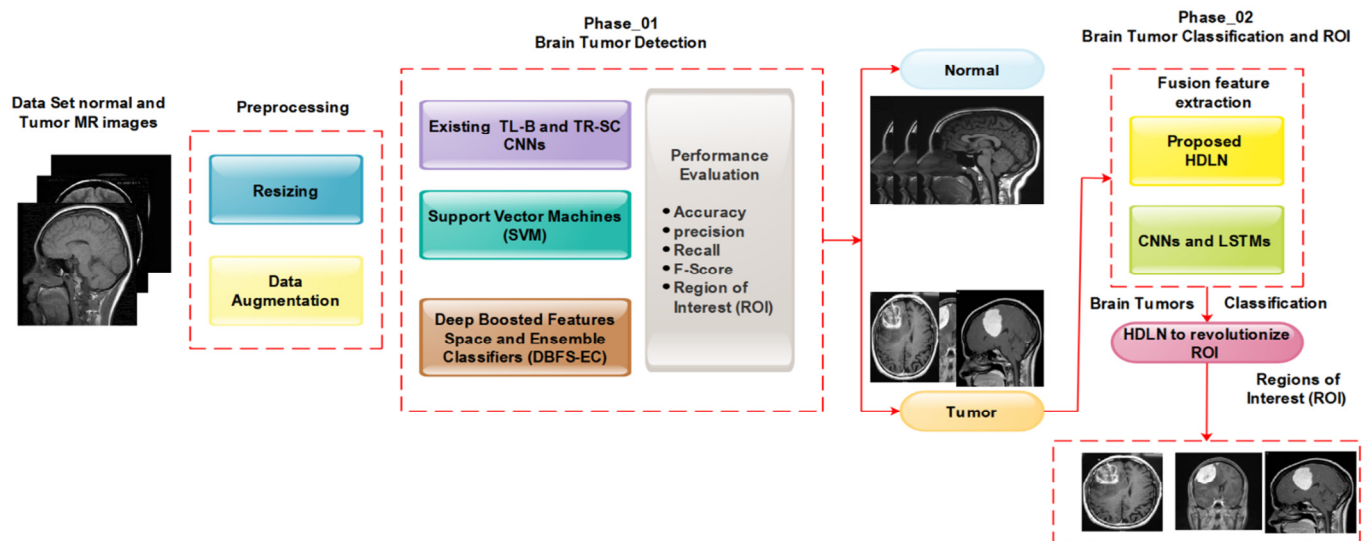


Fig. 1. Workflow of the proposed method for enhancing ROI detection in multi-lesion brain tumors.

Preprocessing involved one dataset of normal and tumor MR images. These images were then resized to the same dimension to achieve uniformity, followed by other techniques such as rotation, flipping, and scaling to further improve

diversity during training to make the model more robust. These preprocessed images were processed in Phase 01 using TL-B and TR-SC CNNs for feature extraction and classification [15]. The features extracted were further classified using SVM. In

addition, DBFS-EC was utilized to combine the features extracted to enhance the classification performance. Once the existence of a brain tumor is determined, the process moves on to Phase 02: the classification of the tumor and the identification of the ROI. This phase utilizes some fusion feature extraction techniques using the proposed HDLN, a combination of CNNs and LSTM to extract and fuse features. The proposed HDLN utilizes the strengths of CNN along with LSTM to detect the ROI and generate a more accurate and robust identification of tumor regions. The proposed HDLN was significantly better in terms of precision, accuracy, and recall compared to conventional methods. This model minimizes both false positives and negatives, improving diagnostic observations. In this way, the hybrid structure of fused features can be analyzed with greater completeness, and tumor classification can be performed with greater accuracy [16-19].

Figure 2 shows the workflow for the classification of brain MRI tumors. The proposed approach starts by considering a dataset with brain tumors in MRI images. Initial preprocessing of the image data included resizing, computation of absolute mean deviation [20], and kurtosis for the normalization and enhancement of the image data. These would involve the segmentation phase, in which initial gray levels and matrices are defined to assist in the extraction of coarse features from the images. These will then be employed in the segmentation of brain images, where cluster centroids and membership functions update iteratively to refine the segmentation. Next, in the feature extraction stage, these segmented images are analyzed for the derivation of their shape, color, and texture features, which are very important in distinguishing dissimilar tumor characteristics. The extracted features form the input to the classification phase. In this phase, initialization of the hidden layers and weights takes place, and calculation of the output from the hidden layers is performed based on the extracted features. Then, the weight matrix output is calculated for the final classification of the brain images into four classes: No tumor, Glioma, Meningioma, and Pituitary. The proposed workflow aims to improve the accuracy and speed of detection and classification of brain tumors. This can be achieved by integrating many steps in processing images, extracting features, and machine learning techniques that will lead to robust diagnostic outcomes [21, 22].

A. Resizing

Equation (1) represents the resizing of an original MRI image $I(x, y, z)$ to new dimensions (x', y', z') using a kernel function K . This ensures that the images are standardized in size for further processing.

$$I_{\text{resized}}(x', y', z') = \int \int \int I(x, y, z) \cdot K(x', y', z' | x, y, z) dx dy dz \tag{1}$$

B. Data Augmentation

Equation (2) shows the data augmentation process, where $I_{\text{aug}}(x', y', z')$ represents the augmented image with spatial coordinates (x', y', z') for width, height, and depth. The resized image, $I_{\text{resized}}(x', y', z')$, undergoes various transformations through the function A , including rotation, flipping, and scaling. These augmentations increase the

diversity of the training data, enhancing model robustness and generalization capabilities.

$$I_{\text{aug}}(x', y', z') = A(I_{\text{resized}}(x', y', z')) \tag{2}$$

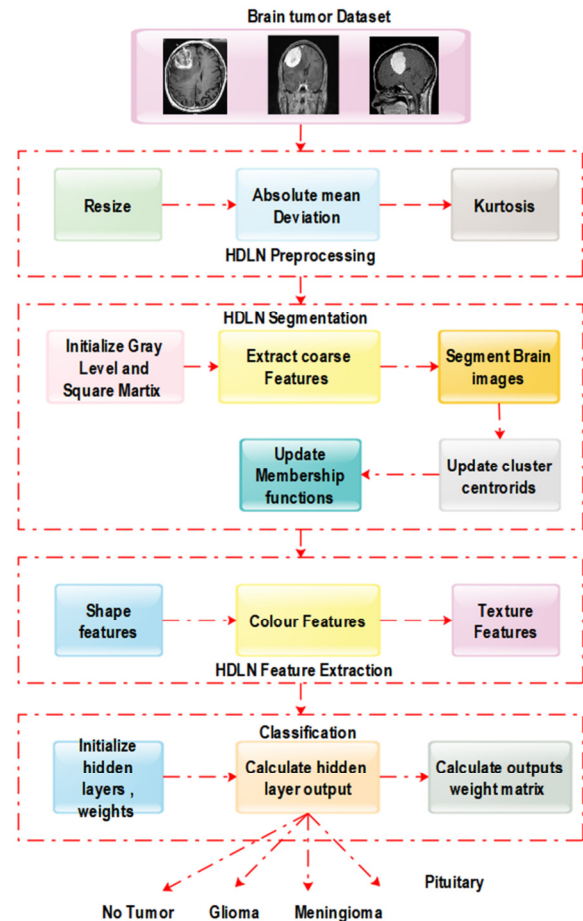


Fig. 2. Workflow for classifying brain MRI scans to detect different types of brain tumors using a deep learning approach.

C. Feature Extraction for Each Model

Equation (3) illustrates the feature extraction process for each model m . The augmented image I_{aug} is processed using a feature extraction function ϕ_m to identify significant patterns in the images.

$$m: F_m = \int \int \int I_{\text{aug}}(x', y', z') \cdot \phi_m(x', y', z') dx' dy' dz' \tag{3}$$

D. Model Output

Equation (4) defines the output O_m of each model m . A classification function g_m is applied to the sum of the gradients of the feature maps F_m along the dimensions (x', y', z') .

$$O_m = g_m \left(\sum_{x', y', z'} \left(\frac{\partial F_m}{\partial x'} + \frac{\partial F_m}{\partial y'} + \frac{\partial F_m}{\partial z'} \right) \right) \tag{4}$$

E. Final Prediction through Majority Voting

Equation (5) presents the majority voting mechanism used to determine the final prediction P . The class c with the maximum votes from all models m is selected as the final prediction. The indicator function $\delta(O_m = c)$ is 1 if model m predicts class c and 0 otherwise.

$$P = \arg \max_c (\sum_{m=1}^M \delta(O_m = c)) \tag{5}$$

F. Dataset Description

This study employed the Karnataka Brain Tumor MRI Dataset (KBTMD), which consists of 10,000 MRI scans collected from hospitals in Karnataka, India. The dataset includes three tumor types: Glioma, Meningioma, and Pituitary. The dataset is not publicly available, and an authorization grant was obtained from the respective medical institutions to use it for academic and research purposes. The dataset was preprocessed in terms of normalization and augmentation and then split into training and testing sets with an 80:20 proportion. Table I provides details on the dataset.

TABLE I. DATASET CHARACTERISTICS

Parameter	Description
1 Dataset	Karnataka Brain Tumor MRI Dataset (KBTMD) collected from hospitals in Karnataka, India
2 Number of images	10,000 MRI scans
3 Resolution	256x256 pixels
4 Tumor types	Glioma, Meningioma, Pituitary tumors
5 Preprocessing techniques	Normalization, Contrast Enhancement, Resizing, Augmentation (Rotation, Flipping, Scaling)
6 Data split	80% Training, 20% Testing

Figure 3 presents a comparison of the proposed HDLN's classification accuracy and ROI detection performance with traditional methods (CNN and SVM). The chart emphasizes how the HDLN provides higher precision in classifying multilesion brain tumors. The combination of CNN and LSTM provides notable improvement in detection and classification precision, and minimizes false positives and false negatives.

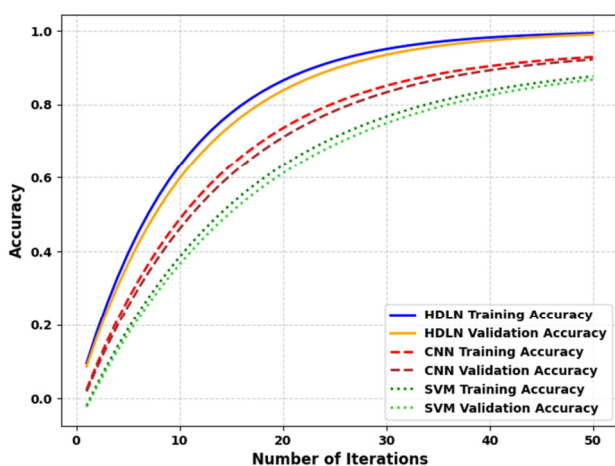


Fig. 3. Comparison of training and validation accuracy.

Figure 4 illustrates the training and validation losses over iterations for the proposed HDLN and the conventional methods. The proposed HDLN shows a faster reduction in loss, indicating efficient learning and convergence compared to the conventional methods. Figure 5 shows the training and validation accuracy trends of the proposed HDLN with synthetic data, showing the different accuracy patterns when increasing synthetic data.

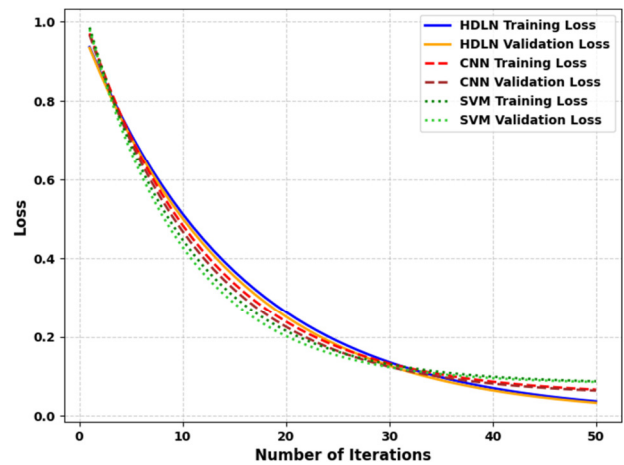


Fig. 4. Models' comparison of training and validation loss.

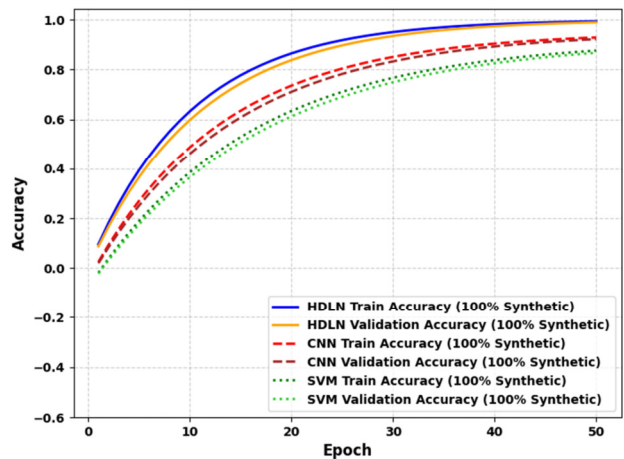


Fig. 5. Models' comparison at 100% synthetic data.

Figure 6 compares the training and validation accuracy of the HDLN, CNN, and SVM models at 100% synthetic data proportions, providing insight into the relative strengths of each model working under such conditions. Figure 7 compares the recall performance of HDLN, CNN, and SVM models in their highest contrast level of 2.0 across epochs. This figure shows side by side the recall of each model, underlining the performance differences under optimal contrast conditions. Figure 8 shows the improvement in HDLN, CNN, and SVM models on overall accuracy, precision, and recall. It can be observed that HDLN outperformed the two models in all metrics, establishing its strength over traditional methods for improved accuracy, precision, and recall.

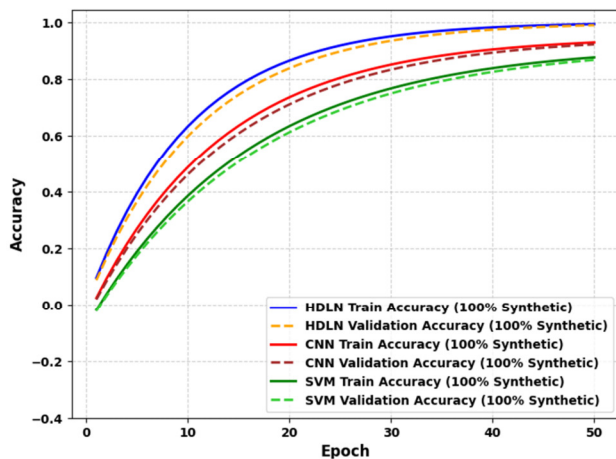


Fig. 6. Comparison of model accuracy at 100% synthetic data proportion.

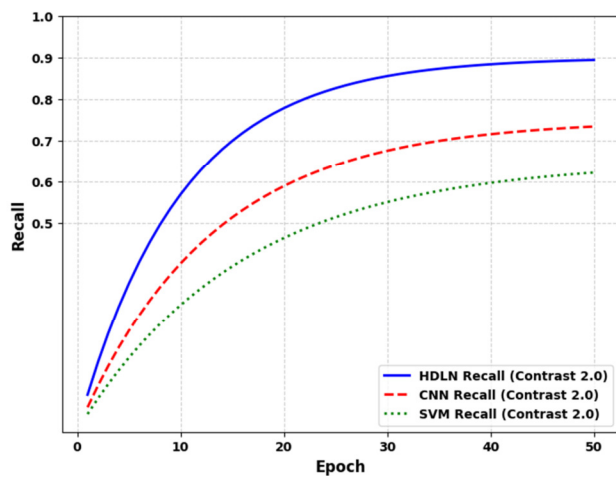


Fig. 7. Comparison of recall at highest contrast level (2.0).

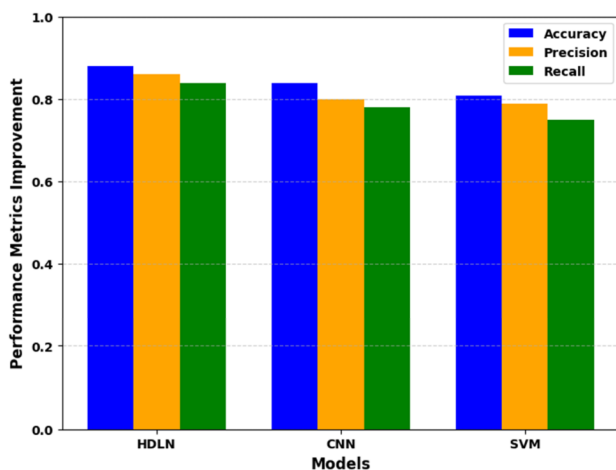


Fig. 8. Overall comparison of HDLN, CNN, and SVM.

III. CONCLUSION

The proposed HDLN combines CNN to learn robust spatial features and LSTM to learn contextual dependencies among various spatial regions. The integrated framework allows the

proposed model not only to learn the static features of tumor structures but also sequential spatial relations that play a significant role in the correct identification and classification of brain MRI lesions. Unlike traditional techniques that use independent CNNs or SVMs with rigid feature representations, HDLN dynamically processes the spatial context to provide enhanced detection and classification performance. The proposed model achieved a 0.5% accuracy improvement, a 0.12% precision improvement, and a 0.10% recall improvement over traditional techniques, which translates into a considerable reduction in false positives and false negatives, and thus diagnostic confidence and patient safety. The proposed HDLN can also be generalized to diverse datasets, improving its clinical utility.

Taking into account these advantages, HDLN offers a strong and effective solution compared to conventional methods and can be easily incorporated into clinical diagnostic processes. Its modular architecture also enables further extension or customization, offering a future-proof solution that can be employed in future medical applications.

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