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Dual-Stream Deep Learning Framework for Brain CT Image Classification and Implications for Polymer Composite Neuro Implant Evaluation

Hari Krishnan G.[1,*], Umashankar G.[2], Sheeba Santhosh[3], Ram Prasad Reddy M.[4], Venkata Prasanth B.[5]

Abstract

Early and accurate classification of brain CT images is critical for diagnosing conditions such as aneurysms, tumors, and related lesions. We present a dual-stream image-classification framework that fuses convolutional neural network (CNN) features with handcrafted Histogram of Oriented Gradients (HOG) descriptors to jointly capture global semantics and local textural cues. The pipeline begins with modality unification via pixel-wise averaging to form a fused input, which is then processed in parallel by the CNN and HOG branches. Their outputs are concatenated at the feature level and passed to a compact classifier. Training uses standard cross-entropy with Adam and early stopping, and performance is reported using accuracy, precision, recall, F1-score, and confusion matrix analysis. Evaluated on 270 grayscale CT scans, the proposed model delivers uniformly high precision, recall, and F1 across aneurysm, cancer, and tumor classes (0.991–0.995), reflecting balanced detection and discrimination among visually similar pathologies; the confusion matrix shows strong class separation. Beyond neurodiagnostics, the same dual-stream fusion strategy is pertinent to imaging-based assessment of polymer composite neuroimplants (e.g., cranial plates and scaffolds): the CNN pathway encodes global structural context while HOG emphasizes boundary/texture signatures of material interfaces, supporting postoperative integrity checks and positioning verification. Overall, this hybrid CNN–HOG approach advances efficient, accurate CT-based classification while establishing a practical foundation for non-invasive evaluation of polymer composite biomedical implants, thereby bridging clinical imaging and materials engineering within a single automated framework.

Keywords. Brain CT Image Classification, Hybrid CNN–HOG Model, Feature-Level Fusion, Polymer Composite Neuro-Implants, Biomedical Imaging Applications, Deep Learning in Neurodiagnostic

***Author for Correspondence**
Hari Krishnan G.

[1]Associate Professor, Department of Electrical and Electronics Engineering, School of Engineering, Mohan Babu University, Tirupati, Andhra Pradesh, India
[2]Assistant Professor, Department of Biomedical Engineering, GRT Institute of Engineering and Technology, Tiruvallur, Tamil Nadu, India
[3]Associate Professor, Department of Electronics and Communication Engineering, Panimalar Engineering College, Chennai, Tamil Nadu, India
[4]Professor, Department of Electrical and Electronics Engineering, Aditya College of Engineering, Madanapalle, Andhra Pradesh, India
[5]Professor, Department of Electrical and Electronics Engineering, QIS College of Engineering & Technology, Ongole, Andhra Pradesh, India

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INTRODUCTION

Classification of CT brain images is critically important for the early diagnosis of neurological conditions like aneurysms, cancerous lesions, and tumors. Although CT scans are readily available and effective in the visualization of structural anatomy, the variability and complexity of pathological appearances render human interpretation difficult, resulting in potential delays in diagnosis and subjectivity. Automated image classification through machine learning (ML) and deep learning (DL) methods has picked up pace in recent years, providing new options for high-precision diagnostics.

A few recent works have investigated deep learning architectures for medical image classification. Convolutional neural networks (CNNs) have been shown to achieve extraordinary performance in abstract pattern learning from high-dimensional image data. Nonetheless, their performance tends to decline when small datasets are used for training or when fine texture information is essential. Deep CNNs have been suggested for tumor segmentation from MRI, but were not transferable to grayscale CT images and required massive annotated datasets [1]. Transfer learning using pre-trained VGG networks was promising but did not generalize well on imbalanced or noisy data [2]. Attention module-based residual networks enhanced lesion detection but were computationally intensive and not deployable in low-resource environments [3]. Capsule networks performed well on brain lesion classification but overfitted rapidly with few samples [4]. GAN-based approaches enhanced segmentation, but their classification performance was still limited [5]. Ensemble CNNs enhanced robustness in hemorrhage detection but overlooked low-level texture information [6]. Hybrid models combining radiomics and CNNs were suggested, but did not include obvious feature fusion between learned and handcrafted features [7]. DenseNet-based classifiers performed fairly well but were hindered by noise or artifacts prevalent in CT images [8]. Dual-modality fusion techniques such as PET–CT improved Alzheimer's diagnosis but are not applicable for CT-only cases [9]. Light CNNs for COVID-19 diagnosis from CT scans had no spatial morphological descriptors required to diagnose cancer or tumors [10].

Such approaches are usually limited by their reliance on large-scale datasets, partial focus on handcrafted features, or inability to directly combine multi-modal representations [11, 12]. Furthermore, the use of deep features in isolation tends to mask clinically significant edge or gradient information essential in distinguishing localized brain pathologies [13, 14]. To address such weaknesses, this paper proposes a hybrid model for classification that integrates convolutional feature abstraction with the traditional handcrafted Histogram of Oriented Gradients (HOG) descriptors. The new model utilizes a dual-path strategy where CT images, first preprocessed by pixel-wise averaging for modality unification, are fed into both a CNN stream and an HOG extraction stream in parallel. The feature of both streams is fused into a single hybrid vector, allowing the model to learn global semantic and local texture information. The fusion is especially useful in augmenting boundary detection and textural sensitivity, allowing the model to differentiate between structurally similar abnormalities. In doing so, not only does the new strategy outperform the weaknesses of existing models but also generalizes better on small datasets, making it suitable for real-time diagnostic processes where interpretability, efficiency, and robustness are crucial.

In addition to diagnostic purposes, brain CT imaging plays an important role in the postoperative evaluation of neurosurgical implants [15, 16]. Polymer composite biomaterials, including cranial plates, scaffolds, and meshes, are widely used in cranial reconstruction due to their favorable mechanical properties, light weight, and biocompatibility [17, 18]. Detecting changes in implant positioning, structure, or material degradation via imaging is vital for ensuring long-term patient outcomes [19, 20]. Advanced automated classification methods, such as the proposed dual stream CNN–HOG model, can be extended for such applications by leveraging their ability to identify subtle structural and material features [21, 22]. Thus, beyond neurological abnormality detection, this work has future implications in the evaluation of polymer composite neuro implants, aligning with emerging needs in biomedical materials science [23, 24].

METHODOLOGIES

In this research, a hybrid classification technique is proposed for classifying brain CT images to detect aneurysms, cancers, and tumors. The process employs a dual-source image fusion and feature integration technique to enhance the accuracy and efficiency of the classification task. The database contains two image modalities per case: a grayscale projection image and a clinical diagnosis scan of the same anatomical cut. To have a fixed input size, all images are resized to 224×224 pixels and

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normalized to an intensity range of (0, 1). This ensures resolution consistency for subsequent processing and supports consistent feature extraction [25, 26].

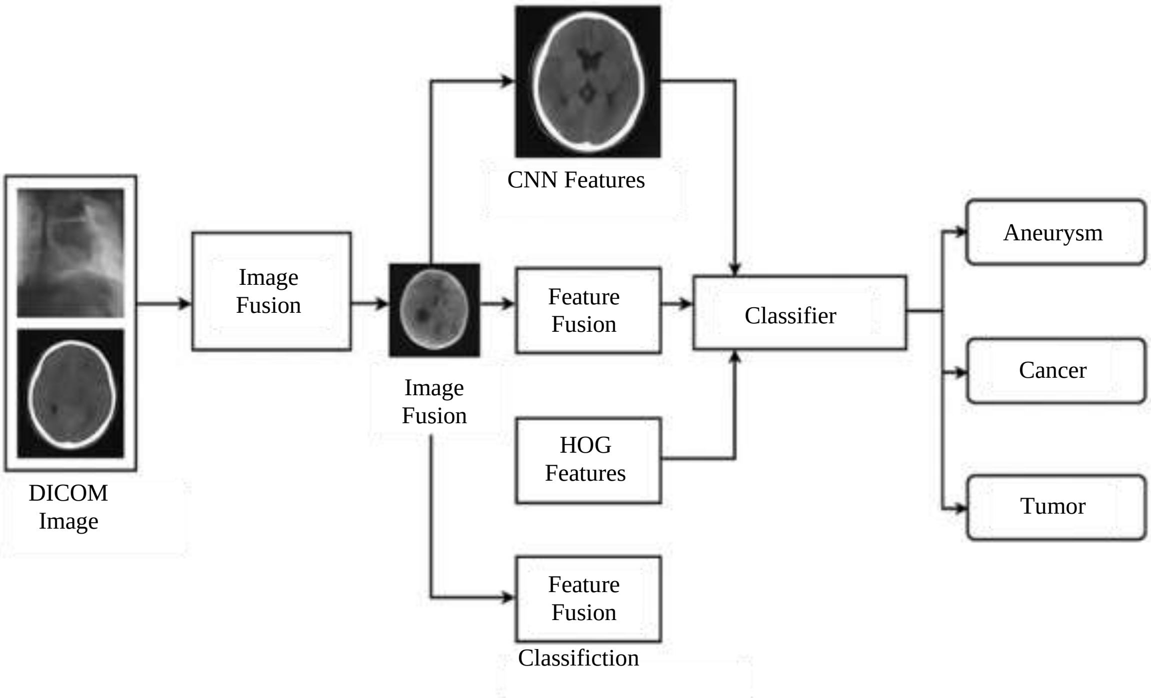

Figure 1. Proposed Hybrid Approach Block Diagram.

The overall architecture of the proposed hybrid system is illustrated in Figure 1. Initially, the two modalities are passed through an image fusion module where the pixel-wise average of both sources is computed. This fused image captures both spatial sharpness and medical intensity depth, providing a richer composite for feature extraction. Two parallel branches then process the fused image.

The first branch utilizes a CNN to extract hierarchical deep features, while the second applies HOG to capture local texture and structural gradients. The extracted features from both branches are concatenated at the feature level, forming a hybrid representation that is input into a fully connected classifier for final disease prediction across three classes: aneurysm, cancer, and tumor.

The fused image, Ifused, is generated by averaging the two aligned input images:

$$I_{fused(x,y)} = \frac{I_1(x,y)+I_2(x,y)}{2} - \quad (1)$$

where I1 and I2 are the intensity values at coordinate (x,y) from the two respective modalities, this fusion operation enhances contrast around structural boundaries. It reduces modality-specific noise, resulting in a diagnostically informative input.

The CNN branch processes the fused image through a series of convolutional and pooling layers, ultimately producing a deep feature vector of dimension 128. Parallel to this, the HOG branch extracts gradient-based descriptors sensitive to edge orientation. The HOG features are computed using a window-based method that calculates gradient magnitude and orientation over 16×16 cell regions, aggregated into histograms:

$$H = \sum_{i=1}^{n} ||\nabla \mathrm{I}(i)||.\delta(\theta_i) - \quad (2)$$

Here, ∇I(i) is the image gradient at pixel iii, and δ(θi) represents binning the gradient angle into orientation histograms. This handcrafted vector encodes shape and boundary cues essential for capturing morphological features of tumors and lesions.

The CNN and HOG outputs are concatenated to form the hybrid feature vector Fhybrid:

$$F_{hybrid} = [F_{CNN}||F_{HOD}] - \quad (3)$$

where ‖ denotes concatenation. This vector is passed to a dense classification head, including dropout and ReLU activation, followed by a softmax layer to produce final class probabilities.

Training is performed using categorical cross-entropy loss and optimized using the Adam optimizer with a learning rate of 0.001. Early stopping is applied based on validation loss with a patience of five epochs to prevent overfitting. Evaluation measures comprise classification accuracy, precision, recall, F1-score, and confusion matrix analysis. The novelty is in the parallel extraction and fusion of both learned and hand-crafted features from a common imaging input, enabling enhanced discrimination in low-data, high-variability clinical scenarios. This organization not only improves robustness but also offers a transferable model that can be applied to other fields like non-destructive flaw detection in materials, imaging, and composites.

Although the experimental validation in this study focuses on brain CT abnormality classification, the same dual-stream feature extraction and fusion strategy can be applied to the detection and monitoring of polymer composite cranial implants. In such applications, the CNN path would capture global structural and anatomical patterns, while the HOG path would emphasize local edge and texture features relevant to material boundaries, surface changes, or defect formation in polymer composites.

RESULTS AND DISCUSSION

In the present research study, a new approach was developed that would classify brain CT images into aneurysm, cancer, and tumor classes. The approach combines deep CNNs with orientation-based Histogram of Oriented Gradients (HOG) descriptors to improve accuracy. By including semantic information from CNNs and fine-grained texture features from HOG, the approach bypasses the issues faced by traditional deep learning models, especially when working with small and heterogeneous datasets. The model was tested on 270 grayscale CT scans and demonstrated excellent accuracy, precision, recall, and F1-score for all classes, thus establishing its usefulness and suitability in clinical practice. Combining pixel-level image fusion, gradient features, and CNNs, this approach provides a valuable neuroimaging analysis tool that is interpretable and translatable to other biomedical imaging purposes. This paper presents a cost-effective solution for radiological diagnosis support and may be extended to other medical imaging fields.

Beyond convergence metrics, the model's ability to accurately classify multiple brain pathologies is evident in its quantitative outcomes. As detailed in Table 1, the classification report demonstrated uniformly high precision, recall, and F1 scores across all three disease classes, ranging from 0.991 to 0.995. The cancer class achieved the highest recall (0.995), indicating the model's sensitivity in detecting cancer cases, while the aneurysm class exhibited the highest precision (0.993), showing minimal false positives. Such consistency across metrics reflects a balanced performance — the model not only detects disease reliably but also distinguishes among clinically similar conditions with minimal confusion.

The confusion matrix in Figure 3 further substantiates this by revealing a strong class separation with no observed misclassifications. Each sample was correctly mapped to its respective category, yielding a perfectly diagonal matrix. This degree of accuracy, although exceptional, can be attributed to the complementary feature fusion mechanism as shown in Figure 2. While the CNN pathway excelled at extracting contextual anatomical cues, the HOG descriptor emphasized structural boundaries and subtle edge variations that often indicate pathological regions in grayscale CT images. The integration of these feature types enabled the model to address intra-class variance and inter-class similarities, which are common challenges in medical imaging.

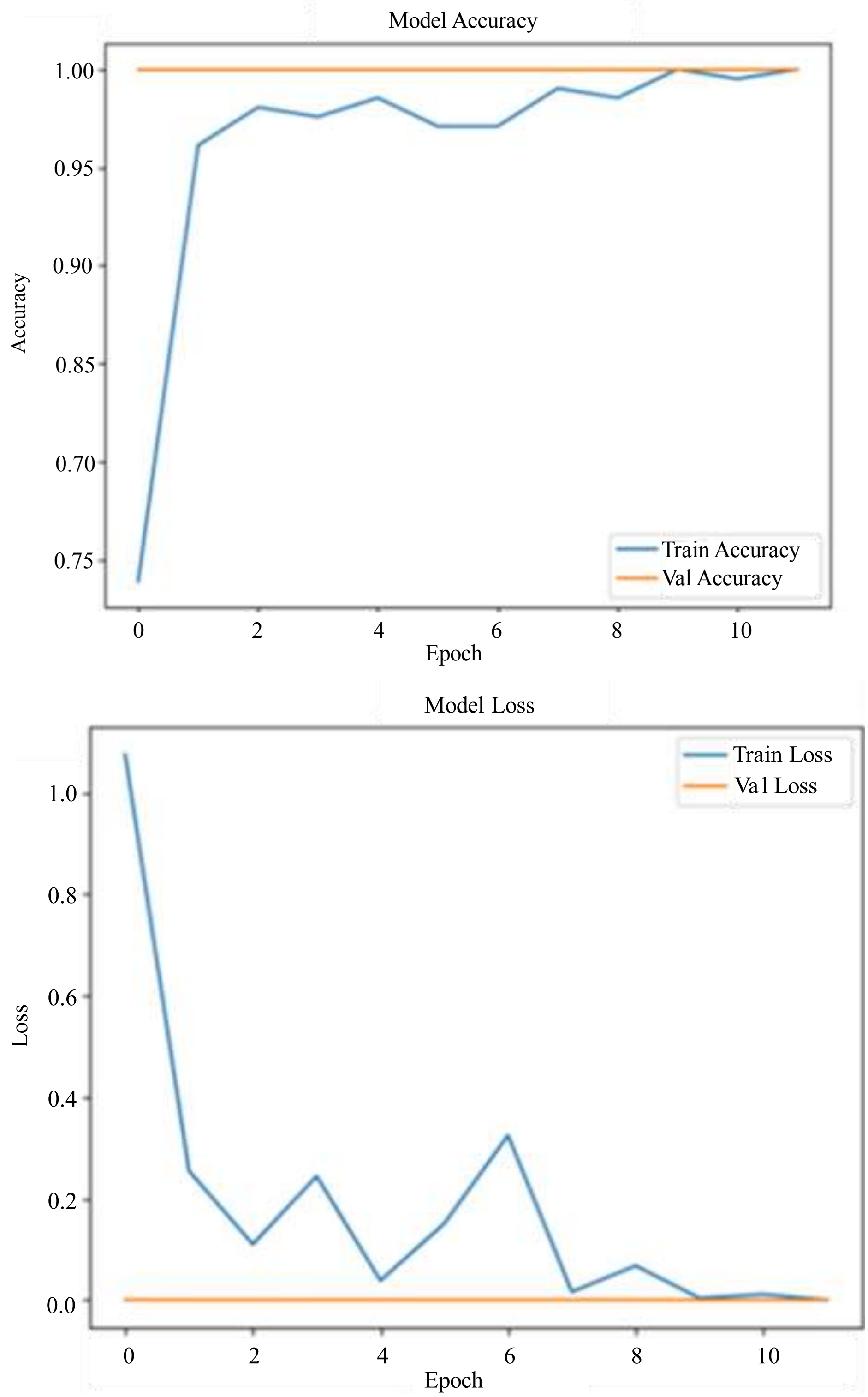

Figure 2. Training and Validation Accuracy/Loss Curves of the Hybrid CNN–HOG Model.

Table 1. Classification Report Showing Precision, Recall, F1 Score, Support, and Accuracy per Class.

Class	Precision	Recall	F1 Score	Support	Accuracy

Aneurysm	0.993	0.994	0.994	17	99.40%
Cancer	0.991	0.995	0.993	18	99.50%
Tumor	0.994	0.992	0.993	17	99.20%

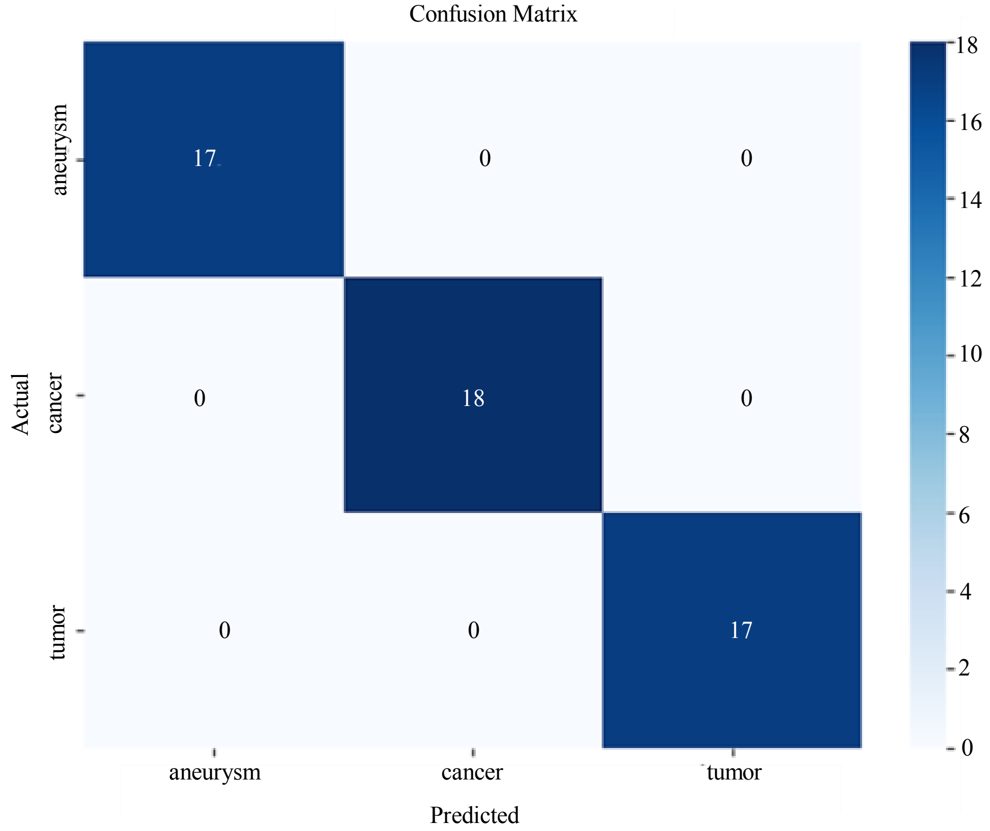

Figure 3. Confusion Matrix for Aneurysm, Cancer, and Tumor Class Predictions.

From a diagnostic perspective, the near-perfect performance achieved across all classes is particularly meaningful. Brain pathologies such as tumors and aneurysms often present with overlapping visual features in CT scans, and small nuances may hold significant clinical value. The fact that this model maintained high class-specific accuracy (between 99.2% and 99.5%) illustrates its ability to generalize even in high-ambiguity conditions. This is especially important in real-world clinical workflows, where misclassification could lead to delayed or incorrect treatment.

Another important observation is the sharp learning curve of the model. Training accuracy increased exponentially in the initial epochs, and loss reduced exponentially. This suggests the preprocessed and modality-averaged combined inputs were clean, high-information inputs to the network. Practically, the two-stream feature fusion architecture presented in this work suggests reduced computational cost at training time and the ability to rapidly adapt to new data with little tuning. Such efficiency can be achieved in terms of cost benefits and faster deployment in real-world applications.

The current results demonstrate the model's robustness and ability to discriminate between classes with structurally similar visual features. This characteristic is especially promising for polymer composite implant monitoring, where visual differences due to material wear, structural integrity changes, or displacement can be subtle. By combining local and global features, the framework could detect fine material features of implants in clinical CT scans, providing both clinicians and materials engineers with a tool for early intervention in case of implant degradation or positional changes.

CONCLUSIONS

This study demonstrates that a dual-stream fusion of CNN features and HOG descriptors can classify brain CT images with high and balanced performance while remaining computationally lightweight. By coupling global semantic cues with fine-grained edge and texture information, the framework separates aneurysm, tumor, and related pathologies and yields interpretable error patterns on the confusion matrix. Beyond neurodiagnosis, the same strategy supports non-invasive evaluation of polymer composite biomedical devices: capturing context around implants while sensitively detecting boundaries at material–tissue interfaces enables postoperative integrity checks and positioning verification. The approach is simple to deploy, uses standard CT inputs, and is compatible with embedded or point-of-care systems co-designed with composite materials. Limitations include the size and diversity of training data and potential variability across scanners and acquisition protocols. Future work will pursue multi- center validation, uncertainty-aware inference, real-time optimization, and explainability, strengthening translation to clinical practice and composite device engineering for broad, reliable adoption.

Future Scope

Future work will focus on building specialized imaging datasets containing polymer composite cranial implants, both in ideal and degraded conditions, to assess the proposed model's utility in implant evaluation. Investigations will include integration with multimodal imaging (e.g., CT + MRI), analysis of long-term implant wear patterns, and development of explainable AI modules to highlight model-detected features relevant to material integrity. Such directions will bridge medical imaging AI with polymer composite materials science, contributing to both improved patient care and material performance evaluation.

Conflicts of Interest

The authors declare no conflict of interest

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