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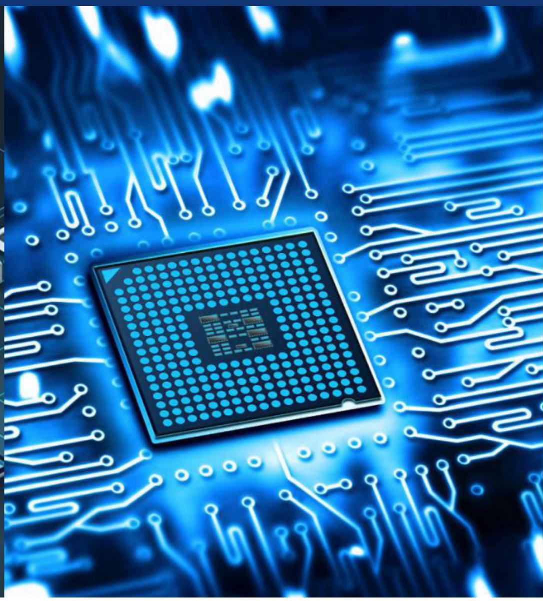


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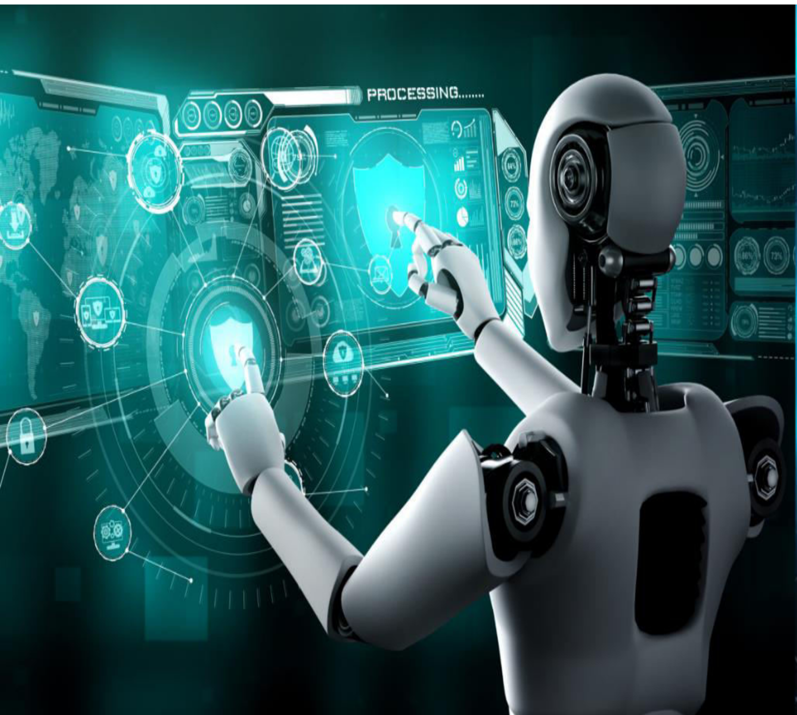

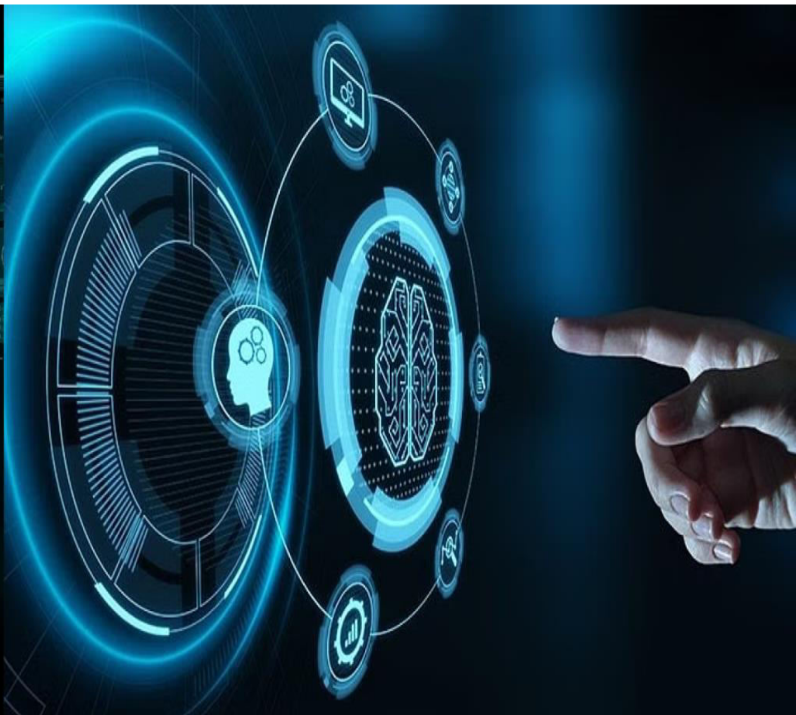

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Enhancing Burn Severity Assessment with Deep Learning: A Comparative Analysis and Computational Efficiency Evaluation

Mr. Dharaneshkumar M L, Kushal Kumar G, Pushpanjali B H

Assistant Professor, Department of Artificial Intelligence & Data Science, C.I.T, Gubbi, Tumkur, India

UG Student, Department of Artificial Intelligence & Data Science, C.I.T, Gubbi, Tumkur, India

UG Student, Department of Artificial Intelligence & Data Science, C.I.T, Gubbi, Tumkur, India

ABSTRACT: This paper describes a comparative study of eight deep learning models to assess the stage of burn severity on small datasets of 2D images. The models include variations on Convolutional Neural Networks (CNNs), attention based CNNs, and hybrid combinations with machine learning classifiers like Support Vector Machine (SVM), Random Forest (RF), and eXtreme Gradient Boosting (XGBoost). The main aim of this study is to classify burns according to the degree of inflammation, scarring, pigmentation, and uniformity based on images captured with either digital cameras or smartphones. Special emphasis was put to computational efficiency, evaluated on the basis of FLOPS and MACs. Decision fusion models with attention-based CNNs achieved the highest accuracy (95%) with elevated computational load.

KEYWORDS: Burn severity assessment, Deep learning, Convolutional Neural Network (CNN), Attention-based models, Decision fusion, Computational complexity, VGG16 hybrid models, Medical imaging, Image classification, Inflammation and pigmentation analysis, Scarring assessment.

I. INTRODUCTION

Burn injuries are a significant public health problem across the globe and contribute to about 180,000 deaths per year, in addition to a great number of non-fatal cases with long hospital stays, permanent bodily damage, and disability. Effective treatment of burn injury depends significantly on a proper assessment of the specific burn conditions as this aids clinicians in directing their decisions and predicting possible complications. Traditionally, clinicians would estimate the severity of a burn by visually estimating the TBSA involved and by inspecting the wound for parameters such as depth and damage to tissue. The limitations of this method included considerable variability in the opinion among the clinician and a tendency to overestimate TBSA; some studies have shown that visual assessment can be up to 6% overestimated. This visual estimation associated error can therefore create suboptimal treatment considerations and delay recovery of the patient in hand.

Formulating a computer-aided technique for assessment was necessary. This method was perceived as more accurate, objective, and consistent. Deep learning has enormous promise for medical image analysis, with reliable data-driven solutions surpassing conventional visual estimation. The earlier studies in burn severity assessment dealt with advanced imaging techniques, including ultrasound and terahertz spectroscopy, but none have access to the expensive and highly specialized equipment in some settings. This study aims to fill that technology gap by including deep learning models for the analysis of a limited number of simple 2D burn images, mostly gleaned from the deep learning models for simple 2D burn image analysis from widely available cameras and smartphones.

To extend the limits assigned to conventional burn assessment approaches, this study presents a unified burn scoring system which assesses images according to four principal features: inflammation, scar formation, uniformity, and pigmentation. For the analysis of these attributes, various deep learning models are used: these include CNNs, attention based CNNs that focus on critical regions of the image, DF models that combine predictions by multiple models to enhance accuracy,s and hybrid models that employ feature extraction using a pre-trained VGG16 model together with

ML classifiers, such as RF, SVM, and XGBoost. Each model was engineered to evaluate particular aspects of burn severity so that more exact classification results could be presented.

The computational cost analysis provided will serve us an insight on how efficiently the models perform, by giving the FLOPS and MACs to refer resource demand for every approach of our model. By finding the trade-off between the accuracy of the model and its computational efficiency, the study in its essence provides practical insight on which models might be best placed for real-time clinical application with limited resources. Thus, the comprehensive approach would not only suffice to ensure robust improvements in classification rates with regards to burn severity but the ensured practicality of such methods across a free range of clinical environments.

II. RELATED WORK

1. Burn Severity Assessment: Older works around burn severity assessment with machine or deep learning used different approaches but came down to terahertz spectroscopy and ultrasound imaging. For present purposes, however, certain authors like Khani et al. have applied SVM, Naïve Bayes, and Linear Discriminant Analysis to classify burn severity on the basis of spectroscopic data. Such methods include the use of specific imaging devices that are often not accessible. While some have applied CNNs and transfer learning on photographic images, results strongly depend on the size of the dataset, which represents an important challenge in medical imaging.
2. Skin Cancer Detection: Classification approaches discussed for skin cancer detection are similar to those for burn severity assessment. Approaches like transfer learning (EfficientNet, Inception, ResNet, VGG) and ensemble approaches give insights for applying deep learning to burn severity classification.
3. Deep Learning Techniques:

- CNNs: The convolutional layers in CNNs are employed to extract hierarchical features from images. CNNs have found their applications in different medical image classification problems, including lung disease detection, brain hemorrhagic identification, and skin cancer.
- Autoencoders: Well known for dimensionality reduction, autoencoders provide meaningful representations for classification. Applications span from brain tumor detection to Alzheimer's classification.
- VGG16: A 16-layer CNN model used as a feature extractor in hybrid models. The authors exploit VGG16's capabilities in the combination with SVM, RF, and XGBoost for classification.
- Attention Mechanism: This makes CNNs better by allowing the model to focus on selected important regions in the image, leading to improved interpretability and accuracy.
- Decision-Level Fusion: A technique for fusing predictions from different models, this almost invariably performs better than the individual classifying models.

III. PROPOSED ALGORITHM

A. Design Considerations:

- **Datasets**: 2D color images from different patients.
- **Data source**: Collected from the Children's Hospital of Michigan, Detroit, MI, USA, over two phases.
- **Phases**: Phase-I and Phase-II datasets.
- **Medical Ethics**: Approved by DMC & WSU IRBs (protocol #051717MP4X).
- **Data Privacy**: All data de-identified.
- **Data Composition**: Datasets include images with multiple affected areas showing varying burn severity levels.
- **Image Cropping**: Each affected region cropped and treated as a separate image for AI model training and evaluation.
- **Labels**: Four categories for burn severity assessment: Inflammation, Scar, Uniformity, Pigmentation.
- **Training & Testing Split**: Intra-patient and inter-patient divisions (testing includes images from both the same and different patients).

B. Description of the Proposed Algorithm:
The framework for burn severity classification consists of four main stages: Data Pre-processing, Data Augmentation, Classification using Deep Learning Models, and Model Evaluation.

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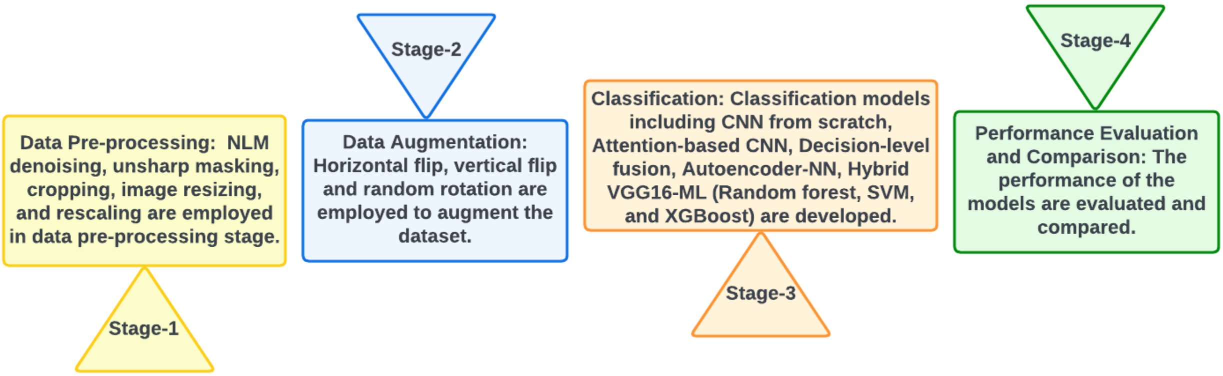

FIGURE 1. Step-wise design of the proposed framework for burn severity classification

IV. METHODOLOGY

The methodology used for this study included: data categorization.

Images were acquired from burn patients who were treated at the Children's Hospital of Michigan in two different phases. They were anonymized to ensure that patient data would not be identified. Images were labeled by a team of four experts in burn management and enlisted as per inflammation, pigmentation, scarring, and homogeneity. The data were preprocessed according to this, beginning with NLM denoising: this was for reducing noise without deterring the details too much. The denoise.nl.means function in scikit-image was applied with parameters like patch size, distance, and noise standard deviation in order to tune denoising.

Unsharp Masking: increases the contrast of the edges, and included features are more visible. The unsharp masking formula controls the sharpness level:

V=XLPF+γ×(X−XLPF)V=X LPF+γ×(X−X LPF).

FIGURE 2. Results obtained from NLM denoising and unsharp masking

Data augmentation involved horizontal flipping, vertical flipping, and random rotation to produce a wider variety of training data that results in more robust models.

1. Model architectures:

- CNN and Attention: Attention-based CNN are afforded attention to the specific zones of the image through channel and spatial attention modules, thereby improving classification accuracy.
- Autoencoder-NN: Encoder-decoder architecture for dimensional reduction and classification.
- Hybrid VGG16-ML: A new approach that combines VGG16 training with machine learning classifiers (RF, SVM, and XGBoost).

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2. Training metric and evaluation:

- Adam optimizer, Sparse Categorical Cross-Entropy loss: An 80:20 train-test split.
- Metrics include accuracy, Big O Notation, FLOPS, and MACs, with precision in training and evaluation.
- Decision fusion thus combines output predictions from three different models through weighted averaging and majority voting methodologies.

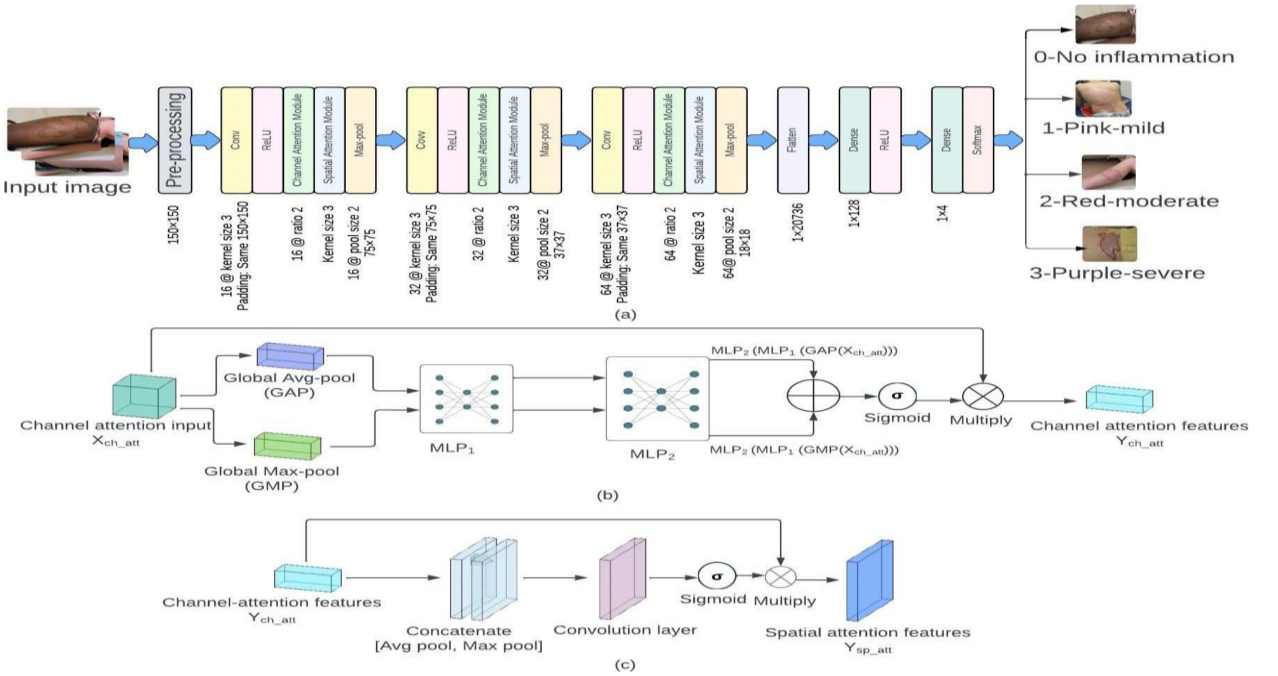

FIGURE 3. (a) Framework for Attention-based CNN model (b) Channel attention module (c) Spatial attention module

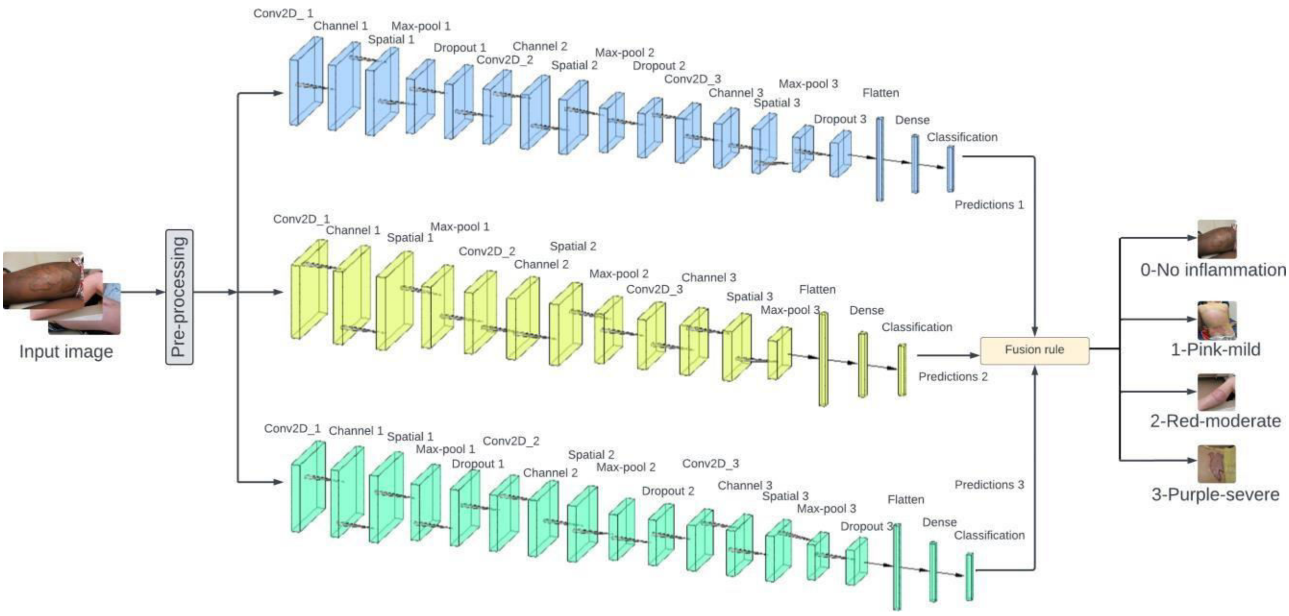

FIGURE 4. Framework of the decision-level fusion model

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V. SIMULATION RESULTS

Datasets	Characteristics	Classes	Attn CNN 1	Attn CNN 2	Attn CNN 3	**Best DF accuracy**
Phase-I	Inflammation	4	0.94	0.98	0.93	**0.98**
	Scar	4	0.93	0.94	0.93	**0.94**
	Uniformity	2	0.96	0.98	0.96	**0.98**
	Pigmentation	4	0.88	0.84	0.86	**0.88**
Phase-II	Inflammation	2	0.96	0.96	0.96	**0.96**
	Scar	2	0.95	0.96	0.95	**0.96**
	Uniformity	2	0.95	0.88	0.94	**0.96**
	Pigmentation	2	0.95	0.94	0.93	**0.95**

TABLE 1. Performance of Decision fusion With Attention-based CNN models

Datasets	Characteristics	Classes	CNN 1	CNN 2	CNN 3	**Best DF accuracy**
Phase-I	Inflammation	4	0.88	0.91	0.92	**0.91**
	Scar	4	0.90	0.89	0.90	**0.90**
	Uniformity	2	0.88	0.90	0.90	**0.91**
	Pigmentation	4	0.75	0.86	0.85	**0.88**
Phase-II	Inflammation	2	0.87	0.90	0.90	**0.91**
	Scar	2	0.88	0.89	0.90	**0.91**
	Uniformity	2	0.90	0.90	0.89	**0.90**
	Pigmentation	2	0.87	0.89	0.89	**0.90**

TABLE 2. Performance of Decision fusion With CNN models

Datasets	**Characteristics**	**Classes**	**LDA** [7]	**CNN** [13]	**Attn. CNN** [93]	**DF-CNN**	**DF-Attn. CNN**	**Auto-encoder NN**	**VGG16-RF**	**VGG16-SVM**	**VGG16-XGBoost**
Phase-I	Inflammation	4	0.86	0.88	**0.98**	0.95	**0.98**	0.92	0.70	0.80	0.80
	Scar	4	0.61	0.90	**0.94**	0.90	**0.94**	0.90	0.68	0.82	0.80
	Uniformity	2	0.51	0.88	**0.98**	0.93	**0.98**	0.90	0.62	0.81	0.81
	Pigmentation	4	0.82	0.75	0.84	**0.88**	**0.88**	0.86	0.60	0.79	0.79
Phase-II	Inflammation	2	–	0.87	**0.96**	0.91	**0.96**	0.87	0.65	0.80	0.81
	Scar	2	–	0.88	**0.96**	0.91	**0.96**	0.89	0.60	0.79	0.80

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	Uniformity	2	–	0.90	0.88	0.91	**0.96**	0.88	0.61	0.77	0.78
	Pigmentation	2	–	0.87	0.94	0.90	**0.95**	0.87	0.61	0.75	0.76
Average Accuracy			0.70	0.87	0.93	0.90	**0.95**	0.87	0.63	0.792	0.79
±STD (Avg. Acc)			±0.14	±0.04	±0.04	±0.01	**±0.02**	±0.03	±0.03	±0.02	±0.01

TABLE 3. Performance comparison of different models

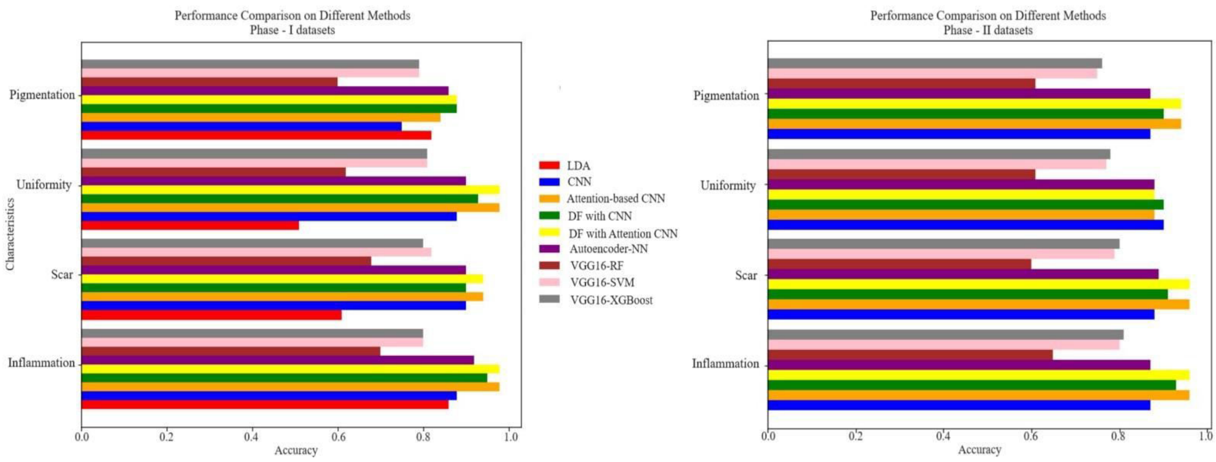

FIGURE 5. Visual performance comparison of the proposed models on Phase-I and Phase-II datasets

VI. CONCLUSION

The study concludes that deep learning-a means of improving burn severity assessment through decision fusion models with attention mechanisms-offers durable support for the improvement of burn severity assessment. These models feature superior classification accuracy (95%) by selecting the right features reflecting the severity like inflammation, scarring, pigmentation, and uniformity. Still, these large models were computationally expensive and recommended highly for high-resource situations. Whereas the attention-based CNN model did provide a balanced option with good accuracy (93%) and less computational cost for resource-poor settings, which means attention mechanisms could offer better performance in diagnostics without the challenge of fusion. Further work will be concentrated on deploying a larger dataset, exploring multi-imaging solutions, and forms of models that optimize accuracy by also keeping computational complexity low in an effort to make strides in advanced burn severity assessment to bring it to wider use in the clinic.

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