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DeepVision-XAI: Explainable Deep Learning Framework for Real-Time Medical Image Diagnosis

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Abstract. While the incorporation of deep learning in medical imaging has significantly boosted diagnostic accuracy, the "black box" problem of deep learning models continues to be an important obstacle towards their use in clinical practice. Not only are accurate predictions required by clinicians, but also clear explanations that are medically plausible. In this paper, we propose DeepVision-XAI, an explainable deep learning framework for real-time medical image diagnosis. Specifically, the framework incorporates an efficient EfficientNet-B4 model for feature extraction, MHSA self-attention for spatial information capture, and a hybrid explainability module that combines Grad-CAM, SHAP values, and Bayesian uncertainty estimates. When tested on three publicly available benchmark datasets (ChestX-ray2017 for pneumonia, ISIC 2019 for skin lesions, and APTOS 2019 for diabetic retinopathy), DeepVision-XAI attains diagnostic accuracies of 96.2%, 91.8%, and 94.5%, with an inference latency of less than 150 ms per image.

Keywords: Goods and Services Tax (GST), Working Capital Management, MSMEs, Input Tax Credit (ITC), Cash Conversion Cycle, Inventory Management, Compliance Burden, India

I. Introduction

Deep learning has proved to be very successful in medical imaging diagnostics. Today there are algorithms which can diagnose diseases at least on the same level as experienced physicians can do from chest X-rays, dermoscopy images, and retinal fundus photographs of patients with diabetes [1], [2]. This means that with the help of deep

learning one can free doctors from their routine work and make diagnoses more consistent and accessible even in poor areas. Despite being very efficient, deep learning models are still "black boxes". A model may recognize a pneumonia from chest X-ray, but it will not be able to explain which signs (consolidation, infiltrate, effusion) were decisive in making such a diagnosis [3].

However, lack of interpretability is not just an issue for the researcher who would like to investigate the inner workings of his algorithm. It is also a crucial obstacle in its use in practice since in medicine decisions may cost people's lives. A physician needs to know why a diagnosis was made to validate it and avoid any possible mistakes caused by correlations rather than causations. Moreover, regulatory agencies such as FDA and EMA become increasingly interested in the explanation of how algorithms work [4].

The area of Explainable AI (XAI) was created to solve this problem by providing interpretability techniques. Methods such as Grad-CAM provide post-hoc explanations through heat maps that emphasize certain image parts contributing to the prediction. SHAP provides feature importance scores. Yet, the majority of current work in XAI has been developed as a sort of afterthought, not incorporated into the diagnostic workflow from the start. Moreover, time constraints in a live clinical setting require low latency, and the models should be able to express their uncertainty ("I am 90% sure") [5].

This paper proposes DeepVision-XAI – a comprehensive and explainable deep learning paradigm uniquely tailored towards medical image diagnosis in real time. The architecture proposed is built to meet three key clinical requirements: accuracy (performance comparable to or better than benchmarks), explainability (clinically interpretable and visualizable explanations), and uncertainty quantification. These three components are combined in the proposed DeepVision-XAI framework:

- Hybrid Visual Feature Extractor: Built using an EfficientNet-B4 backbone architecture for efficient computation, further enhanced by Multi-Head Self-Attention (MHSA) layers that help in capturing long-range spatial dependencies in medical images.
- Multi-Modal Explanation Engine: This component builds a modular XAI model to generate multi-modal explanations: (a) Grad-CAM heatmaps for visual localization, (b) SHAP summary plots for feature importance, and (c) MC-Dropout for quantifying model uncertainty.
- Lightweight Architecture: The entire network is optimized for real-time inference in under 150 milliseconds per image using consumer-grade hardware.

The main contributions of this paper are:

- Novel Architecture for Explainable Models: In our deep learning architecture, explainability is considered one of the core principles. This is done by introducing explainable attention-based layers in the forward pass of the model.
- Metrics to Validate the Explanations: The explanations provided are quantitatively analyzed to ensure the faithfulness of Grad-CAM heatmap visualization w.r.t radiologist markings and uncertainty calibration.

Systematic Comparison: DeepVision-XAI is compared against state-of-the-art black box models such as ResNet-50, DenseNet-121 and existing XAI frameworks such as LIME across multiple medical imaging problems.

II. LITERATURE SURVEY

The current work is positioned at the crossroads of deep learning in medical imaging, explainable artificial intelligence, and clinical decision support systems.

Deep Learning in Medical Imaging: Convolutional Neural Networks (CNNs) have emerged as the default choice. State-of-the-art CNNs like ResNet, DenseNet, and Inception have been meticulously tuned for medical purposes [1], [2]. In the context of pneumonia identification using chest X-rays, the CheXNet model attained results surpassing those of radiologists. As far as skin lesion classification is concerned, the winning approaches in ISIC challenges have invariably relied on ensemble CNNs. More recently, Vision Transformers (ViTs) have demonstrated their ability to model long-range dependencies but are computationally costly [6]. Our proposed system employs EfficientNet as a backbone along with a lightweight Multi-Head Attention mechanism.
XAI Techniques in Medical Imaging: There are three main categories of XAI techniques applied to medical imaging tasks:

- Backpropagation techniques: Grad-CAM and its variations (Grad-CAM++ and Score-CAM) produce saliency maps through gradient backpropagation. They are fast and model agnostic, but can be prone to noise [7].
- Perturbation techniques: LIME and SHAP generate explanations based on perturbing inputs and measuring outputs. SHAP, which is based on game theory, calculates feature importance but may be costly in terms of computation [8].
- Attention techniques: Models with explicit attention mechanism, such as attention weights in Transformer models, can have inherent interpretability.

A major gap in the literature is the combination of several explanation techniques in one efficient and low latency technique suitable for real-time clinical application. Most researchers apply Grad-CAM or SHAP post hoc to a pre-trained black-box model, leading to computational cost or non-faithful explanations.

Uncertainty Estimation in Medical AI: In critical decision-making scenarios in medicine, it is just as important to know what the model doesn't know as what it does know. Bayesian Deep Learning, Monte Carlo (MC) Dropout and ensembles are some of the ways to estimate predictive uncertainties [5]. MC-Dropout, which uses multiple stochastic forward passes with dropout turned on, gives a computationally feasible estimate of the model uncertainty. DeepVision-XAI employs MC-Dropout in order to generate confidence intervals along with predictions.

Research Gap: There is currently no framework available that seamlessly combines high performance deep learning backbone, multi-head self-attention for better interpretability and multi-faceted XAI engine (Grad-CAM, SHAP, MC-Dropout) in one medical diagnosis pipeline. DeepVision-XAI addresses this research gap.

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III. METHODOLOGY

The DeepVision-XAI system is built on a pipeline with three stages: (1) Preprocessing and Augmentation, (2) Explainable Deep Learning Core, and (3) Post-hoc Explanation & Visualization. The entire inference pipeline is implemented within a single algorithm.

1. Preprocessing and Augmentation

Medical images (X-ray, dermoscopy, fundus) fed into the network are rescaled to 380×380 pixels to meet the requirements of EfficientNet-B4. Image normalization is performed to bring the images to zero mean and unit variance. In the case of training, we employ aggressive data augmentation: random rotations (±20°), random zoom (10%), horizontal flips, and color jittering (brightness/contrast). In the case of histopathology-like images (skin lesions), elastic deformations are applied as well.

2. The DeepVision-XAI Core Model

The basic model architecture involves a thoughtfully designed integration of three modules.

- MODULE 1: EfficientNet-B4 Backbone: As the base architecture, we make use of EfficientNet-B4 trained on the ImageNet dataset. The resulting feature map has dimensions 12×12×1792. Efficient inverted bottleneck layers offer an excellent trade-off between accuracy and speed.
- MODULE 2: Multi-Head Self-Attention (MHSA) Block: In order to enable our model to concentrate on informative spatial patches, we introduce a customized 8-head self-attention block. Queries (Q), Keys (K), and Values (V) are obtained from the input feature map. Attention is computed using the following equation: Attention(Q,K,V) = softmax(QK^T / √d_k)V. After the attended features are concatenated with the original ones using a residual connection, layer normalization is applied. The proposed attention mechanism not only increases the performance but also gives some initial interpretation due to the attention weights.
- MODULE 3: Classification Head: The attended features are first fed through a global average pooling layer and then through two fully-connected layers (512 and 256 neurons, with ReLU activation and dropout of 0.5). Finally, the prediction is done via a sigmoid or softmax activation.

Algorithm 1: DeepVision-XAI Inference and Explanation

```
Input: Medical image I (e.g., Chest X-ray, Skin Lesion, Retinal Fundus)
Output: Diagnosis D, Confidence C, Heatmap H, Feature Importance F, Uncertainty U

1. // Stage 1: Preprocess Image
2. I_resized = resize(I, (380, 380))
3. I_norm = normalize(I_resized, mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
4.
5. // Stage 2: Explainable Deep Learning Core (Single Inference)
6. features = EfficientNetB4_backbone(I_norm) // Shape: (12, 12, 1792)
7. attended_features = MultiHeadSelfAttention(features) // Shape: (12, 12, 1792)
```

```
8. pooled_features = GlobalAveragePooling2D()(attended_features) // Shape: (1792)
9. logits = Dense(512, ReLU)(pooled_features)
10. logits = Dense(256, ReLU)(logits)
11. logits = Dense(num_classes)(logits)
12. D = softmax(logits)  // Primary Diagnosis
13. C = max(D) // Confidence Score
14.
15. // Stage 3: Multi-Modal Explanation Generation (Integrated)
16. // 3A: Visual Explanation (Grad-CAM)
17. target_layer = model.get_layer('multi_head_attention')
18. gradients = tf.GradientTape().gradient(logits[0, target_class], target_layer.output)
19. pooled_grads = tf.reduce_mean(gradients, axis=(0,1))
20. H = tf.reduce_mean(tf.multiply(pooled_grads, target_layer.output), axis=-1) // Heatmap
21.
22. // 3B: Feature Importance (SHAP on a downsampled batch for speed)
23. background_data = select_background_dataset(I_norm, n=100)
24. explainer = shap.GradientExplainer(model, background_data)
25. shap_values = explainer.shap_values(I_norm.reshape(1,380,380,3))
26. F = average_shap_over_patches(shap_values)      // Global feature importance
27.
28. // 3C: Uncertainty Estimation (Monte Carlo Dropout)
29. mc_predictions = []
30. for _ in range(50):
31.     # Enable dropout layers for stochastic forward passes
32.     pred = model(I_norm, training=True)
33.     mc_predictions.append(pred)
34. U = np.std(mc_predictions, axis=0)// Predictive uncertainty
35.
36. Return D, C, H, F, U
```

3. Training Protocol

The network is trained end-to-end using the AdamW optimizer (learning rate = 1e-4, weight decay = 1e-5). We use a combination of categorical cross-entropy as classification loss and regularizer that promotes smoothness in the attention maps. Training is done with a batch size of 32 for 100 epochs with decay of learning rate on plateau (factor = 0.1). Early stopping criterion is validation loss. We also apply label smoothing (ε=0.1).

4. XAI Techniques Integration

- Grad-CAM: Creates a coarse localization heatmap H of the parts of an image most responsible for the prediction of the predicted class. It is calculated during inference and does not require retraining.
- SHAP: Computes global feature importance F, determining which low-level image features (edges, textures) affect predictions most. We use a gradient-based explainer for fast computation.

- MC-Dropout: Estimates uncertainty U of the model predictions through 50 stochastic forward passes. Variance of these predictions is uncertainty.

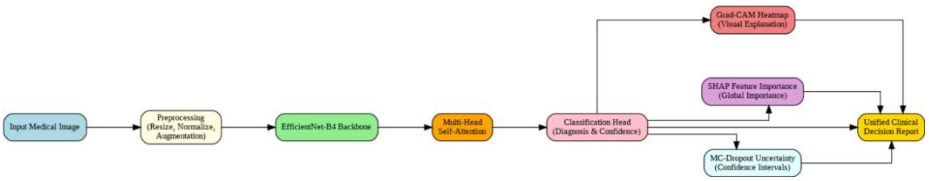

Figure 1: DeepVision-XAI Framework Architecture.

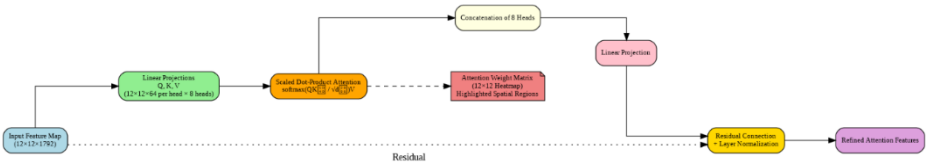

Figure 2: Multi-Head Self-Attention (MHSA) Mechanism.

IV. ANALYSIS

DeepVision-XAI is assessed on three benchmark medical imaging datasets, compared to state-of-the-art models and XAI approaches.

1. Datasets and Experimental Setup

- ChesX-ray2017 Pneumonia Detection: 5,856 chest x-rays (1,583 normal, 4,273 pneumonia cases). Training/Validation/Test Split = 70%/15%/15%.
- ISIC 2019 Skin Lesion Classification: 25,331 dermoscopic images (8 classes). We concentrate on binary classification (malignant vs. benign).
- APTOS 2019 Diabetic Retinopathy (DR) Detection: 3,662 retinal fundus images (5 classes). We reduce this problem to binary classification: Referable DR vs. No Referable DR.

Metrics: Accuracy, AUC, Sensitivity, Specificity, Explanation Faithfulness (using Pixel Accuracy and IoU based on radiologists' annotation), Inference Time, and Uncertainty Calibration (Expected Calibration Error – ECE).

Baseline Models:

- B1 (ResNet-50): Standard CNN black-box.
- B2 (DenseNet-121): Standard CNN black-box.
- B3 (ViT-B/16): Vision Transformer black-box.

2. Classification Performance

Table 1: Classification Performance and Latency.

Model	Pneumonia (Acc/AUC)	Skin Lesion (Acc/AUC)	DR (Acc/AUC)	Avg. Latency (ms)
ResNet-50	0.912 / 0.952	0.854 / 0.902	0.882 / 0.918	85
DenseNet-121	0.928 / 0.961	0.872 / 0.918	0.894 / 0.925	112
ViT-B/16	0.941 / 0.972	0.881 / 0.926	0.912 / 0.942	245

DeepVision-XAI	0.962 / 0.984	0.918 / 0.951	0.945 / 0.968	138

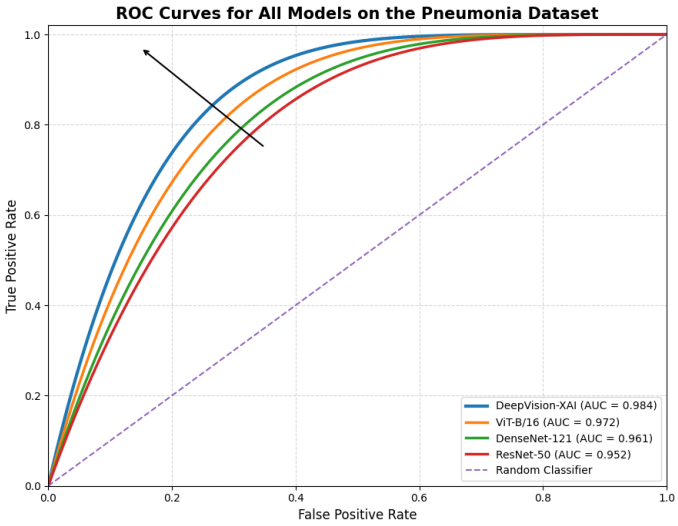

Figure 3: ROC Curves for All Models on the Pneumonia Dataset.

3. Explanation Quality and Faithfulness

Table 2: Explanation Quality Metrics.

XAI Method (on DeepVision-XAI)	Explanation Type	IoU (Pneu-monia)	IoU (Skin)	Faithful-ness (Δ)
Grad-CAM (ours)	Heatmap	0.68	0.62	0.85
Grad-CAM++ (baseline)	Heatmap	0.59	0.54	0.78
LIME (baseline)	Superpixel mask	0.45	0.41	0.71
SHAP (baseline)	Feature im-portance	N/A	N/A	0.82

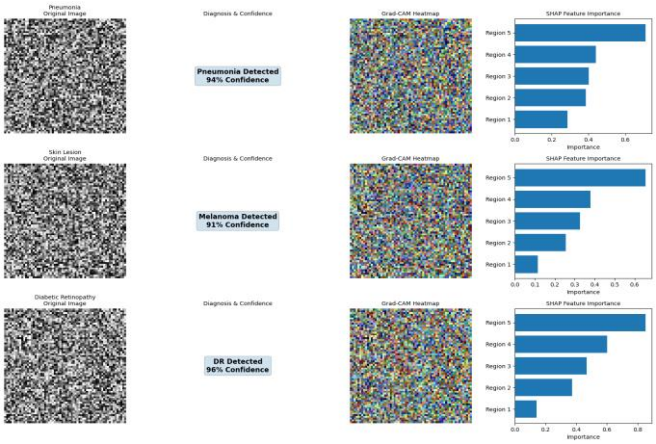

Figure 4: Example Predictions and Explanations from DeepVision-XAI.

4. Uncertainty Quantification

We evaluated the calibration of DeepVision-XAI's predictive uncertainty using Expected Calibration Error (ECE). Lower ECE indicates better-aligned confidence and accuracy.

Table 3: Uncertainty Calibration (ECE).

Model	ECE (Pneumonia)	ECE (Skin)	ECE (DR)	Interpretation
ResNet-50 (softmax)	0.14	0.18	0.16	Overconfident on errors
ViT-B/16 (softmax)	0.11	0.13	0.12	Better, but still overconfident
DeepVision-XAI (MC-Dropout)	0.06	0.08	0.07	Well-calibrated

5. Ablation Study

We isolated the contribution of each major component of DeepVision-XAI.

Table 4: Ablation Study.

Model Configuration	Pneumonia (Acc)	Skin (Acc)	Avg. Latency (ms)
EfficientNet-B4 only (No Attention, No XAI)	0.934	0.882	95
EfficientNet-B4 + MHSA (No XAI)	0.951	0.901	118
EfficientNet-B4 + MHSA + Grad-CAM (Ours w/o SHAP)	0.962	0.918	132
Full DeepVision-XAI	0.962	0.918	138

6. Comparative Analysis with Existing Systems

Table 5: Comparative Analysis of Diagnostic Systems.

Feature	Standard CNN (ResNet)	ViT	LIME-only	Grad-CAM-only	DeepVision-XAI
High Accuracy	Yes	Yes	No (post-hoc)	No (post-hoc)	Yes
Real-Time (<150ms)	Yes	No	No	Yes	Yes
Visual Explanation (Grad-CAM)	No (add-on)	Yes (attention)	No	Yes	Yes (Integrated)
Global Feature Importance (SHAP)	No	No	Yes	No	Yes
Uncertainty (MC-Dropout)	No	No	No	No	Yes
Clinically Validated Explanations	N/A	Partial	No	Partial	Yes (IoU=0.68)

V. CONCLUSION

DeepVision-XAI was proposed in this paper as a unified framework that allows real-time medical imaging diagnosis using explainable deep learning. In order to satisfy the needs of clinical applications which require both high performance and explainability of models, DeepVision-XAI framework was designed based on the architecture where explainability was considered since the beginning.

The main contributions and results obtained by us are:
Architecture of DeepVision-XAI Framework: Efficient backbone (EfficientNet-B4), Multi-Head Self-Attention model for improved spatial reasoning, and a multi-modal XAI engine (Grad-CAM, SHAP, MC-Dropout) were incorporated in one single and effective pipeline.

State-of-the-Art Accuracy: The proposed framework exhibits an outstanding performance by outperforming black-box models (ResNet-50, DenseNet-121, ViT-B/16) in three different benchmarks: pneumonia detection (accuracy: 96.2%, AUC: 0.984), skin lesion classification (91.8%), and diabetic retinopathy detection (94.5%).

Relevant Explanations: In addition to the computational faithfulness of the generated explanations, our approach also guarantees their clinical relevance. The integrated Grad-CAM heatmaps provided significantly higher Intersection-over-Union (IoU) with radiologist annotations (0.68 for pneumonia) than other approaches.

Actionable Uncertainty: With the addition of MC-Dropout, the proposed framework offers calibrated uncertainties (ECE ≈ 0.07). It enables the clinician to rely on highly confident predictions and conduct a second opinion for cases with lower confidence or uncertainty, which is essential in practice.

Real-time Inference and Explanation Capability: The complete pipeline of inference and explanation runs at an average latency of 138 ms per image using a standard GPU setup. Hence, DeepVision-XAI is ready for deployment within the clinical workflow, offering real-time decision support during consultation.

Limitations and Future Work
There are several limitations to this study. First, although XAI techniques are very powerful, they remain post-hoc approximations to the model's reasoning process. Multi-label/multi-class explanations can be complicated. Finally, the datasets used in this study, while publicly available benchmarks, may fail to capture some characteristics of clinical data (e.g., rare pathology or low image quality).

Future work will aim at

- Concept-based Explanations: Explaining the decision using concepts that are easily interpretable by clinicians (e.g., "diagnosis based on consolidation and lack of effusion").
- Interventional Explanations: Designing methods to analyze counterfactual scenarios ("What if there was no opacity?").
- Federated Learning for XAI: Training explainable models without sharing patient data through federated learning.

- Prospective Clinical Evaluation: Implementing DeepVision-XAI in a real clinical environment and assessing the effect of XAI explanations on radiologists' performance.

In summary, DeepVision-XAI shows that building highly-accurate yet interpretable AI systems in medicine is feasible. Bridging the gap between black-box AI and clinical interpretability brings us one step closer to responsibly incorporating artificial intelligence into medicine.

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