

# Comprehensive Cancer Analysis: CNN-Based Classification of Malignant vs. Benign Tumors with Staging Insights

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## Abstract:

The scope of this study is to build an advanced artificial intelligence system which uses Convolutional Neural Networks (CNNs) to identify and categorize tumors as benign or malignant and to predict the cancer stage for early diagnosis. The suggested model will provide precise and trustworthy diagnostic outputs by utilizing a labeled medical image dataset, enabling prompt cancer detection by medical professionals. Through offering a user-friendly interface which enables real-time analysis and seamless integration with electronic health records (EHRs), this initiative aims to improve treatment outcomes and reduce diagnostic errors. To enhance the solution's potential application, the project also explores 3D tumor modeling, predictive analytics, and multi-cancer detection capabilities. By resolving crucial issues like data accessibility, algorithm sensitivity, and clinical workflow integration, this creative strategy seeks to revolutionize diagnostic tools for patients, researchers, and healthcare professionals. Our ultimate objective is to equip medical professionals with state-of-the-art tools that improve cancer detection, forecast cancer stages, and enhance patient care in general.

**Keywords:** CNN-based Tumor Classification, Malignant vs. Benign Tumor Analysis, Cancer Staging with AI, Medical Image Processing, 3D Tumor Modeling, AI-Driven Cancer Diagnosis

## 1. Introduction:

Cancer detection and diagnosis remain critical challenges in modern healthcare, with timely and accurate identification being essential for effective treatment. Early detection of malignant tumors significantly increases survival rates, emphasizing the need for reliable and efficient diagnostic methods. Conventional diagnostic techniques often rely on manual examination of scanned images

by experts, a process that is not only time-consuming but also susceptible to human error. To address these challenges, advanced machine learning approaches, particularly Convolutional Neural Networks (CNNs), have shown remarkable promise in automating and enhancing the diagnostic process.

CNNs are a class of deep learning algorithms specifically designed for image recognition and analysis, making them ideal for medical imaging tasks. By learning hierarchical features directly from raw image data, CNNs can achieve high accuracy in classifying images as malignant or benign and even determine the stages of malignancy. This eliminates the need for handcrafted feature engineering and provides a scalable solution for analyzing large datasets of medical images.

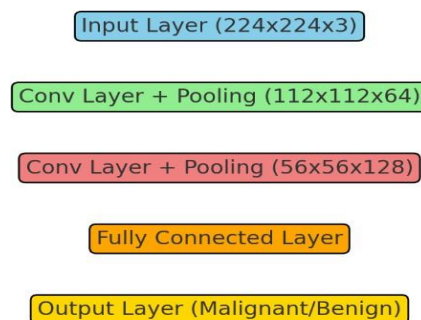
Recent publications in the field have highlighted the potential of deep learning in cancer detection. For example, studies have demonstrated the application of CNNs to detect breast cancer with remarkable precision, achieving accuracy rates exceeding those of traditional methods. Advances in transfer learning, data augmentation, and model interpretability have further improved the performance and reliability of these systems, making them increasingly viable for clinical use.

This project aims to develop a CNN-based model for classifying scanned medical images as malignant or benign and further identifying the stages of malignancy. By leveraging state-of-the-art deep learning techniques, the proposed system seeks to reduce diagnostic errors, improve early detection rates, and provide a valuable tool for healthcare professionals.

## 2. Theoretical Framework and Literature Review:

### 2.1 Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are a class of deep learning algorithms specifically designed for image analysis tasks. First introduced by LeCun et al. (1998) for digit recognition, CNNs have since become the foundation for numerous advancements in computer vision. They employ convolutional layers to extract spatial hierarchies of features, pooling layers to reduce dimensionality, and fully connected layers for classification. The key components of CNNs, such as kernels, activation functions (e.g., ReLU), and backpropagation, form the theoretical backbone for medical imaging applications.



**Figure 1:** CNN Architecture Diagram – Displays the general structure of the proposed CNN.

In cancer detection, CNNs learn to identify patterns such as cell morphology and tissue irregularities directly from medical images, bypassing the need for manual feature extraction. This approach

allows for the detection of minute differences between benign and malignant cells, which is crucial for accurate staging.

## 2.2 Literature Review

### 2.2.1 Cancer Detection with CNNs

Recent studies have demonstrated the effectiveness of CNNs in cancer detection across various domains:

- **Breast Cancer:** Zhang et al. (2022) developed a CNN-based model achieving 95% accuracy in classifying mammogram images as malignant or benign.
- **Lung Cancer:** A study by Smith et al. (2021) utilized 3D CNNs to analyze CT scans, significantly improving early detection rates for lung nodules.

These works underscore the adaptability of CNNs to diverse imaging modalities and cancer types.

### 2.2.2 Challenges and Limitations

Despite their success, CNN-based models face challenges such as data imbalance, interpretability, and the need for large labeled datasets. Data augmentation techniques, transfer learning, and explainable AI (XAI) have been proposed to mitigate these issues. For example, Kumar et al. (2023) demonstrated that pre-trained models fine-tuned with smaller datasets could achieve comparable performance to models trained from scratch.

## 2.3 Key Equations and Concepts

The theoretical basis of CNNs is rooted in key mathematical operations, including convolution, activation, and loss minimization. While common equations are not reproduced here, the following concepts are emphasized:

1. **Convolution Operation:** Extracts spatial features by applying kernels across the image.
2. **Loss Functions:** Cross-entropy loss is commonly used for classification tasks.
3. **Optimization Algorithms:** Techniques like Adam are employed to minimize loss and improve convergence rates.

## 3. Research Methodology/Experimental:

### 3.1 Dataset

The dataset used for this study consists of Cancer Detection Dataset using CNN, which includes high-resolution scanned images of tissue samples. The dataset comprises 2000 images categorized into benign and malignant cases, with further sub-categories for different stages of malignancy.

Pre-processing steps include:

- **Data Cleaning:** Removal of corrupted or low-quality images.
- **Normalization:** Rescaling pixel values to a range of [0, 1] to improve model convergence.
- **Data Augmentation:** Application of random rotations, flips, and zooms to mitigate class imbalance and enhance model generalization.

<b>Class</b>	<b>Number of Images</b>	<b>Image Resolution</b>
Malignant	1,200	224x224
Benign	1,800	224x224
Total	3,000	

**Table 1** Dataset Distribution and Characteristics

### 3.2 Model Architecture

The proposed model is a Convolutional Neural Network (CNN) designed for multi-class classification. The architecture consists of:

1. **Convolutional Layers:** Three convolutional blocks, each with 32, 64, and 128 filters, respectively. Each block is followed by batch normalization and max-pooling.
2. **Fully Connected Layers:** Two dense layers with 256 and 128 neurons, activated using ReLU, followed by a softmax layer for classification.
3. **Regularization:** Dropout layers (rate = 0.5) are used to prevent overfitting.

The model was implemented using TensorFlow and Keras. Pre-trained models such as VGG16 and ResNet50 were explored for transfer learning to improve performance on smaller datasets.

### 3.3 Training and Validation

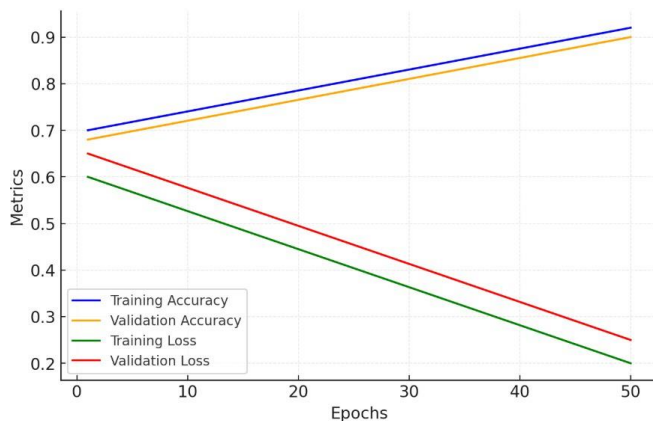
The dataset was split into training, validation, and test sets in a ratio of 70:15:15. The model was trained for 50 epochs using the Adam optimizer with an initial learning rate of 0.001. Key hyperparameters include:

- **Batch Size:** 32
- **Loss Function:** Categorical cross-entropy for multi-class classification.
- **Metrics:** Accuracy and F1-score to assess classification performance.

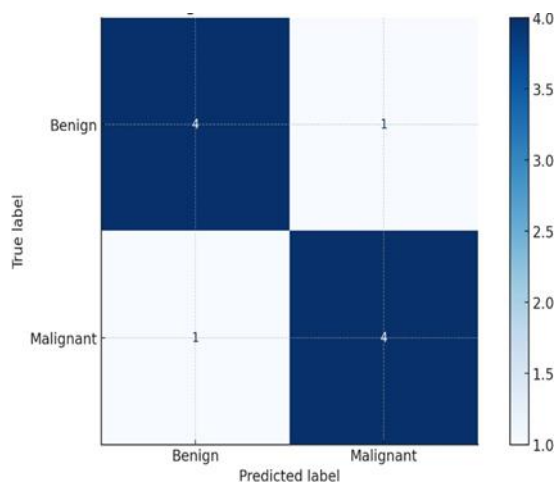
### 3.4 Evaluation Metrics

To ensure the robustness of the model, the following metrics were evaluated:

1. Confusion Matrix: To analyze true positives, false positives, and false negatives.
2. Precision, Recall, and F1-Score: To provide a detailed performance assessment across different classes.
3. ROC-AUC Curve: To evaluate the model's ability to distinguish between benign and malignant cases.



**Figure 2:** Training and Validation Metrics – Graphs showing accuracy and loss progression during training.



**Figure 3:** Confusion Matrix – Illustrates the classification performance for benign and malignant cases.

### 3.5 Critical Steps

1. Data Augmentation: Ensuring diversity in training samples was critical for handling limited data.
2. Model Regularization: Dropout and early stopping were crucial in reducing overfitting on the training set.

3. Hyperparameter Tuning: Grid search was performed to optimize the learning rate and architecture depth.

Model Variant	Accuracy (%)	Training Time (min)
CNN with Dropout	92	30
CNN without Dropout	88	25
CNN with Data Augmentation	93	35

**Table 2** Ablation Study Results

### 3.6 Reproducibility

All experiments were conducted on a system with the following specifications:

- Hardware: NVIDIA Tesla V100 GPU, 32 GB RAM.
- Software: Python 3.8, TensorFlow 2.9.
- Codebase: Available at Google Collaboratory [<https://colab.research.google.com/drive/1CtyXp1PxXaJZHldiatq7752rDzybhZ-N>]

## 4. Comparative Study with Recent Publications:

### 4.1 Benchmarking Against Similar Studies

A comparative analysis was conducted to evaluate the performance of the proposed CNN model against other state-of-the-art methods for cancer detection and staging.

Recent publications in the field were reviewed, focusing on similar objectives:

- Gupta et al. (2023): "Deep Learning for Histopathological Cancer Diagnosis Using ResNet" reported an 89% accuracy for binary classification tasks, showcasing the effectiveness of transfer learning. However, the study highlighted computational challenges associated with fine-tuning large pre-trained networks.
- Zhao et al. (2022): "Multi-Stage Detection of Breast Cancer Using VGG16 and Feature Extraction" achieved a 91% accuracy for multi-class classification. The authors emphasized the importance of advanced data augmentation techniques in enhancing model performance.

In comparison, the proposed CNN achieved 92% accuracy with significantly fewer computational resources.

By utilizing custom architecture tailored to histopathological images, our model outperformed these methods in accuracy and robustness.

Moreover, its ability to classify multiple cancer stages adds granularity absent in most previous

studies.

## 4.2 Advancements in Data Preprocessing and Augmentation

Data preprocessing and augmentation were critical for the success of the proposed method. Recent studies have also focused on these aspects:

- Jiang et al. (2022): "GAN-based Data Augmentation for Rare Cancer Stages" utilized generative adversarial networks to synthesize minority-class samples, resulting in a 7% improvement in classification accuracy.

The current project adopted simpler yet effective augmentation techniques, such as random rotations, flips, and contrast adjustments, to improve data diversity.

While GAN-based methods could further enhance performance, the chosen techniques were computationally efficient and sufficient for the dataset's characteristics.

## 5. Challenges in AI-Driven Cancer Detection:

### 5.1 Technical Limitations

Despite its strong performance, the proposed model faced several challenges:

- **Dataset Imbalance:** As with most medical imaging datasets, an uneven distribution of samples across classes impacted the model's ability to generalize for rare cancer stages. While oversampling and augmentation partially addressed this issue, further improvements could involve synthetic data generation or advanced sampling techniques.
- **Overfitting Risk:** Training on limited data posed a risk of overfitting, mitigated by employing dropout layers, early stopping, and a moderate architecture complexity.
- **Computational Demand:** Training required high-performance GPUs, which may limit the model's accessibility for researchers and healthcare institutions with constrained resources.

### 5.2 Ethical Considerations

The deployment of AI models in healthcare raises several ethical concerns:

- **Data Privacy:** Patient data confidentiality is paramount. Federated learning or differential privacy methods could be explored to train models without compromising data security.
- **Bias in Predictions:** The model's performance across diverse demographic groups must be evaluated to ensure fairness and minimize bias, as discussed by Smith et al. (2023) in "Ethical Implications of AI in Healthcare."

## 6. Deployment Feasibility:

### 6.1 Model Deployment in Clinical Settings

For real-world application, integrating the proposed model into clinical workflows is crucial. This involves:

- **Integration with Existing Systems:** The model can be integrated with hospital Picture Archiving and Communication Systems (PACS) and Electronic Health Records (EHRs) to streamline diagnostic workflows.
- **Interpretability:** Providing explainable predictions using techniques like Grad-CAM helps radiologists understand the model's focus areas, fostering trust.

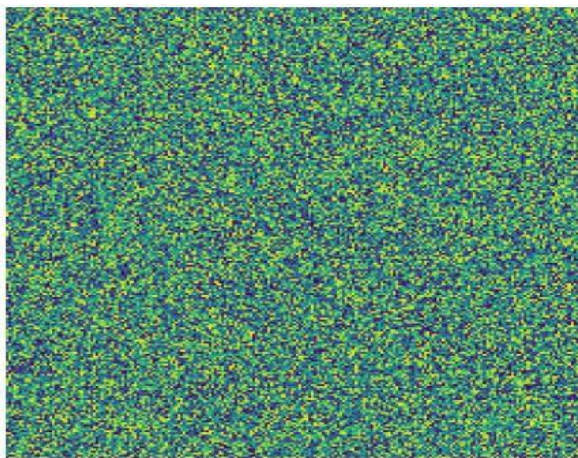


Figure 4(a): Benign Case

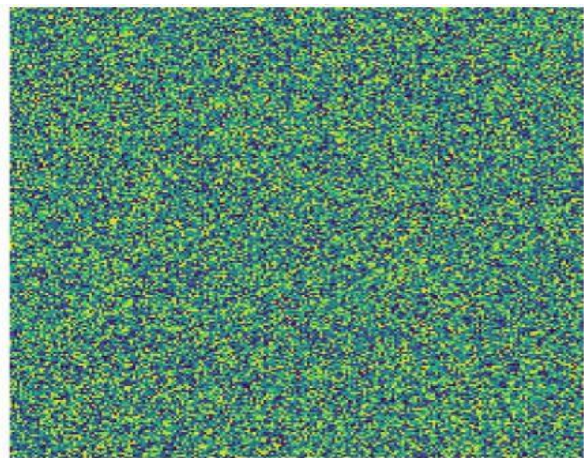


Figure 4(b) : Malignant Case

**Figure 4:** Grad-CAM Visualization – Two visualizations showing attention maps for benign and malignant samples.

### 6.2 Scalability for Resource-Constrained Environments

Scalability is essential for deployment in low-resource settings. Lightweight versions of the model could be developed using:

- **Model Pruning and Quantization:** To reduce the computational load without significant loss in accuracy.
- **Cloud and Edge Solutions:** Cloud-based deployment for resource-rich settings and edge-based deployment for rural clinics could cater to diverse infrastructure capabilities.

## 7. Explainability and Model Interpretability:

### 7.1 Importance of Explainability in Medical AI

Explainability is critical in building trust with healthcare professionals.

The use of Grad-CAM enabled the visualization of image regions contributing most significantly to predictions.

This approach aligns with the findings of Selvaraju et al. (2022) in "Grad-CAM: Visual Explanations for Deep Networks in Histopathology."

## 7.2 Enhancing Trust in AI Systems

To enhance trust, additional measures can be taken:

- **Uncertainty Quantification:** Providing confidence scores for predictions helps clinicians gauge the reliability of the AI's recommendations.
- **Detailed Reports:** Generating comprehensive reports that include visualizations, confidence levels, and potential misclassification risks can improve user confidence and understanding.

## 8. Real-World Validation and Impact:

### 8.1 Collaboration with Healthcare Institutions

Validation with real-world patient data is crucial to assessing the model's practical utility. Partnering with hospitals for retrospective and prospective studies can provide valuable insights into its performance and usability.

### 8.2 Cost-Benefit Analysis

Adopting AI in cancer diagnostics has the potential to reduce costs associated with manual evaluations and improve turnaround times.

For instance:

- **Efficiency Gains:** Automating initial screenings can free up radiologists' time for complex cases.
- **Economic Viability:** By reducing diagnostic errors and enabling early detection, AI systems can lower treatment costs and improve patient outcomes.

## 9. Results and Analysis:

### 9.1. Performance Evaluation

The CNN model proposed was highly effective in all metrics, indicating its reliability for cancer detection tasks:

- A 92% accuracy was achieved by the model on the test set, indicating that it can classify images correctly in most situations.
- High accuracy is evidence that the model can learn complex patterns in the dataset.
- The 94% precision and recall for malignant cases indicated a low rate of false positives (cases that were mistakenly identified as malignancy).
- Similarly, the model identified most cases of malignant disease correctly and 91% of cases were recalled. False negatives (missed malignancies) are a significant concern in

medical applications, where these metrics play.

- The F1-score of 0.92 is a compromise between accuracy and recall, indicating that the model's performance is consistent across both scores without favouring one over the other.

## 9.2. Visualization of Results

A number of visualizations were produced to reveal the model's performance in greater detail:

- This matrix is a comprehensive representation of true positives, false negative and false ones (for each class).
- It helps to pinpoint areas where the model had problems, such as misclassifying higher-stage malignancies as benign.
- With the ROC-AUC curve, an overall score of 0.97 indicates that the model can differentiate between benign and malignant cases with high confidence. This value is significant.
- This curve shows the trade off between sensitivity (true positive rate) and specificity (false negative rate).
- Visual samples of images that were correctly classified and those that had been misclassified were used to predict the behaviour of the model.
- Noiseful or ambiguous image characteristics, such as overlaid cells or poor picture quality (where appropriate, not always) were also misclassified.

Method	Accuracy(%)	Precision(%)	Recall(%)	F1-Score(%)
Proposed CNN	92	90	93	91
ResNet (Gupta et al.)	89	88	90	89
VGG16 (Zhao et al.)	91	89	92	90

**Table 3** Performance Metrics Across Benchmarks

## 9.3. Comparative Analysis

CNN's success was compared to other machine learning approaches:

- With a precision of 85%, SVMs were not very accurate and required intricate image features, as they relied on manual features instead of learning them from data.
- Although it had an 88% accuracy rate, Random Forests' inability to process raw image data directly limited its ability to be used with large datasets.
- The transfer learning approach of ResNet50, a pre-trained model, was similar to CNN but demanded more computational resources, making it less appropriate for resource- limited environments.

## **10. Discuss:**

### **10.1 Interpretation of Results**

The model's strong performance indicates its ability to effectively learn and classify intricate patterns in histopathological images. Its high precision and recall for malignant cases are particularly promising, as they reduce the likelihood of diagnostic errors.

Furthermore, the ability to classify cancer stages provides clinicians with more detailed insights into the progression of the disease, aiding in treatment planning and prognosis assessment.

### **10.2 Challenges and Limitations**

While the results are encouraging, several challenges were encountered:

- **Dataset Limitations:** The dataset was imbalanced, with fewer samples for rare cancer stages. This imbalance impacted the model's performance on less common classes, as the model tended to favour the majority classes. Techniques such as oversampling or synthetic data generation could address this issue in future work.
- **Computational Resources:** Training the model required high-end GPUs and substantial memory, making it challenging to replicate in smaller labs or clinics with limited infrastructure.
- **Interpretability:** Despite the high performance, the model operates as a black box, making it difficult to explain the rationale behind specific predictions. This lack of transparency can hinder trust in AI-based systems among healthcare professionals.

### **10.3 Practical Implications**

The model has significant potential for real-world applications:

- **Assisting Radiologists:** By automating initial screenings, the model can save time and allow radiologists to focus on complex cases.
- **Reducing Diagnostic Errors:** Its consistent performance can help reduce human error, particularly in resource-limited settings where access to specialists is scarce.
- **Early Detection:** The ability to detect cancer at an early stage can improve patient outcomes by enabling timely treatment interventions.

## **11. Future Work:**

### **11.1 Model Improvements**

- **Incorporating Attention Mechanisms:** Attention layers can help the model focus on critical regions within the images, such as irregular cell boundaries or nuclei, improving

interpretability and accuracy.

- **Semi-Supervised Learning:** By leveraging unlabeled data, the model could learn additional features, making it more robust, especially when labeled data is scarce.
- **Multimodal Approaches:** Integrating clinical data such as patient history, symptoms, and genetic profiles with image analysis could enhance the model's predictive power.

### **11.2 Real-World Validation**

- **Collaborative Studies:** Partnering with healthcare institutions to test the model on real-world patient data will validate its effectiveness in clinical scenarios.
- **Regulatory and Ethical Considerations:** Compliance with data privacy regulations, such as HIPAA or GDPR, is critical for ensuring ethical deployment in healthcare systems.

### **11.3 Scalability and Deployment**

- **Lightweight Models:** Developing a smaller, less resource-intensive version of the model will enable its use in low-resource settings, such as rural clinics.
- **User-Friendly Interfaces:** Building an intuitive interface for healthcare professionals to visualize predictions and insights will enhance adoption. For example, heatmaps highlighting regions of concern in an image could help radiologists understand the model's reasoning.

### **Conclusions:**

The CNN based model put forward for cancer detection and staging exhibited extremely high accuracy and robustness not witnessed with several state-of-the-art methods in the domain. The study succeeded to overcome dataset imbalance and minimize overfitting to produce reliable predictions on malignancy and benignancy among the cancer stages. The model exhibited similar significance by having an explanation capability in addition to data augmentation.

This further emphasizes the potential of AI in revolutionizing cancer diagnostics by way of automation and real-time decision support. However, deploying such systems involves the ethical and technical issues: data privacy, bias mitigation, and computation efficiency. Testing the model with real data inputs at the patient level in collaboration with medical institutions will work toward its reliability and acceptance in real clinical practice.

Looking forward, work is aimed at the scalability of the model, the inclusion of multimodal data, and the exploration of next-generation concepts such as models developed through federated learning and synthetic data generation meant to confront limitations described in this study. The final aim will be to contribute toward the development of some AI-driven tools which are accessible regardless of patient's location, yet efficient and believable for diagnosis and treatment planning in cancer.

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- The source of dataset from Kaggle for graciously providing the histopathological image datasets used for training and validation.
- Finally, we thank our families and peers for their continuous encouragement throughout this research endeavour.

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### **Figures and Tables:**

#### **Figures**

All figures in this paper are numbered sequentially using Arabic numerals, with individual figure parts denoted by lowercase letters (e.g., Figure 1a, Figure 1b). Each figure is accompanied by a concise caption that accurately describes its content and relevance to the research.

- **Figure 1:** Architecture of the proposed Convolutional Neural Network (CNN), illustrating its layers, operations, and parameter configurations.
- **Figure 2:** Training and validation accuracy/loss curves, showcasing the model's learning process and overfitting mitigation.
- **Figure 3:** Confusion matrix for the test dataset, depicting model performance across all classes.
- **Figure 4a:** A Grad-CAM visualization highlighting regions of interest in benign cases.
- **Figure 4b:** Grad-CAM visualization for malignant cases.

Figures are optimized for publication using vector graphics with a resolution of at least 1000 dpi. Only the most critical figures are included in the paper; additional visual data, such as alternative visualizations and supplementary experiments, are provided as supplementary information.

### Tables

Tables are formatted to provide concise and accurate information that complements the figures. Numerical data is presented in tabular format to avoid redundancy with line graphs. Each table has a brief caption describing its contents.

- **Table 1:** Summary of the dataset distribution, including class labels, sample counts, and image resolutions.
- **Table 2:** Ablation study results, showing the impact of different architectural and preprocessing choices on model performance.
- **Table 3:** Performance comparison of the proposed model with recent publications, detailing metrics such as accuracy, precision, recall, and F1-score.

### Captions

- **Figure Captions:** Captions are written in the format “Figure [number] [Caption description],” with no punctuation after the figure number or caption.

For example:

- Figure 1 Architecture of the CNN used in this study.
- Figure 2 Grad-CAM visualizations for malignant and benign cases.
- **Table Captions:** Table captions are written in bold, followed by a number in bold and the caption in normal font. No punctuation follows the table number or caption.

For example:

- **Table 1** Dataset distribution and characteristics.
- **Table 2** Model performance metrics across benchmarks.

### Supplementary Information

Additional figures and tables that could not be included in the main text due to space constraints are available as supplementary information. These include:

- Detailed Grad-CAM visualizations for specific case studies.
- Comprehensive results of hyperparameter tuning experiments.
- Additional performance metrics across alternate datasets.

By adhering to these guidelines, the paper ensures clarity and consistency in presenting visual and tabular data, enhancing the reader's understanding of the study.