AI-Driven Skin Cancer Detection: Enhancing Accuracy with Deep Learning Models

PRAYASH DAS
CWID: 20025412

Outline

Introduction

- Skin Cancer is the uncontrolled growth of abnormal skin cells, often caused by excessive exposure to ultraviolet (UV) radiation from the sun or tanning devices.

- **Types**

A. **Basal Cell Carcinoma:** Most common, grows slowly, and rarely spreads.

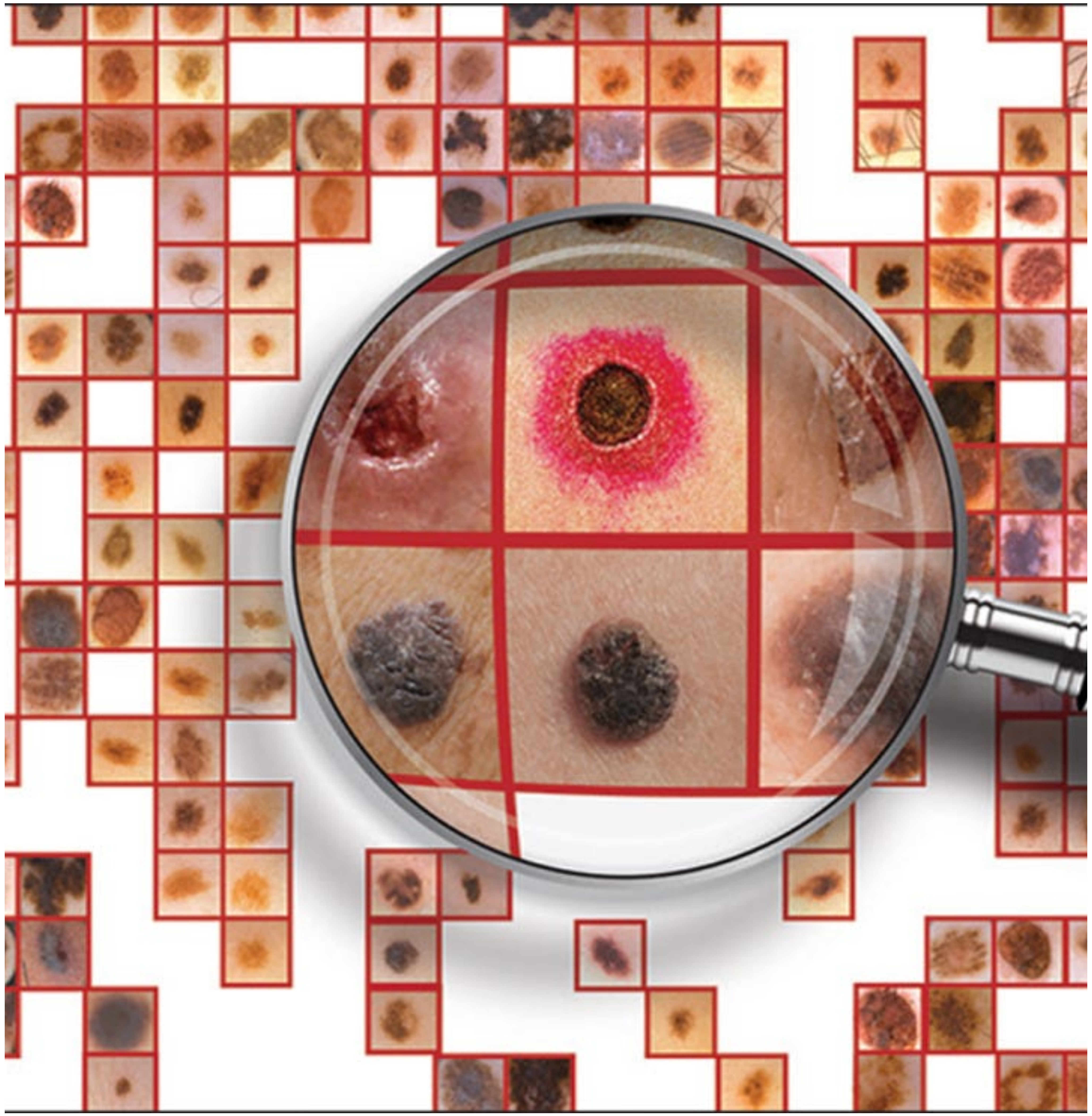
B. **Squamous Cell Carcinoma:** Can spread if untreated.

C. **Melanoma:** Less common but more aggressive and deadly if not detected early.

- Deep Learning leverages neural networks to analyze medical images for the automated detection and classification of skin cancer, enabling early and accurate diagnosis.

- Techniques like **Convolutional Neural Networks (CNNs)** can identify patterns in dermoscopic images, outperforming traditional diagnostic methods in accuracy and efficiency.

- **Advancements:** Deep learning models, trained on large datasets of dermoscopic images, can detect subtle features, aiding in distinguishing between benign and malignant lesions with high precision.



Related Works

- CNNs for Diagnosis: Convolutional Neural Networks (CNNs) achieve dermatologist-level accuracy in classifying skin lesions by learning complex patterns from dermoscopic images.
- Transfer Learning: Pre-trained models like VGG16 and ResNet are fine-tuned for skin cancer detection, improving performance on limited datasets.
- Ensemble Methods: Combining multiple models enhances diagnostic accuracy by aggregating diverse feature extraction capabilities.
- Data Augmentation: Techniques like rotation, scaling, and flipping expand datasets, addressing data scarcity and improving model generalization.
- Explainable AI: Visualization tools (e.g., Grad-CAM) provide interpretability, highlighting regions of interest in images, enabling trust and adoption in clinical settings.
- Segmentation Techniques: Advanced methods like U-Net and Mask R-CNN are used to isolate lesion regions in dermoscopic images, enhancing the accuracy of subsequent classification models.

About the Dataset

- **Source:** The dataset is from the International Skin Imaging Collaboration (ISIC), a leading initiative for skin imaging research. Dataset Link

- **Content:** Contains images of two categories:

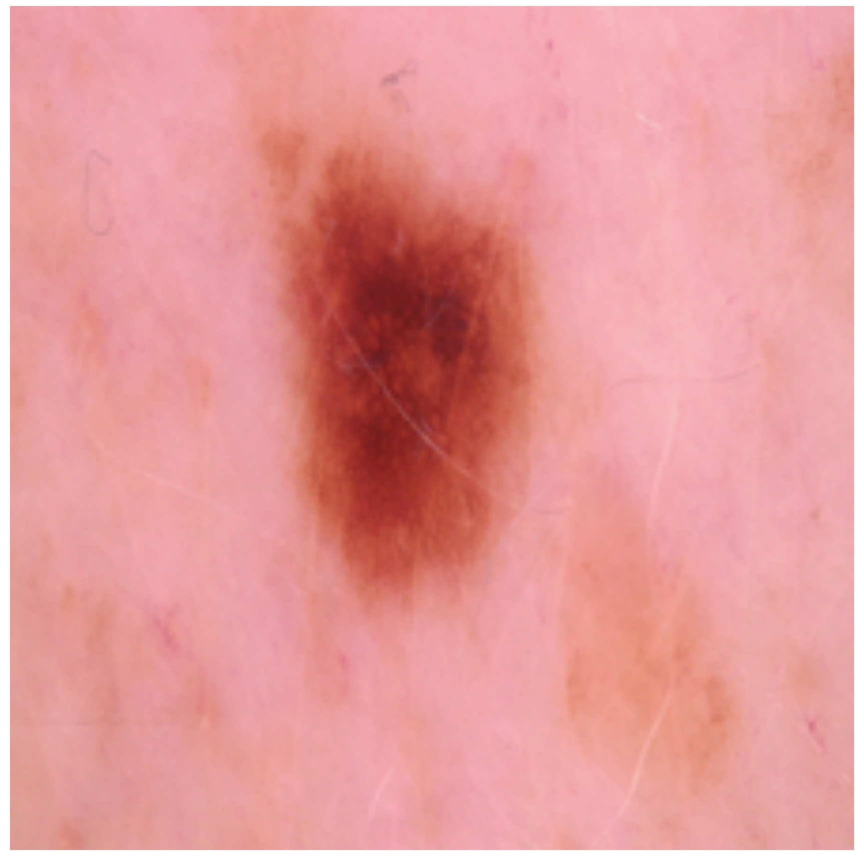
A. **Benign Skin Moles:** Non-cancerous.

B. **Malignant Skin Moles:** Cancerous.

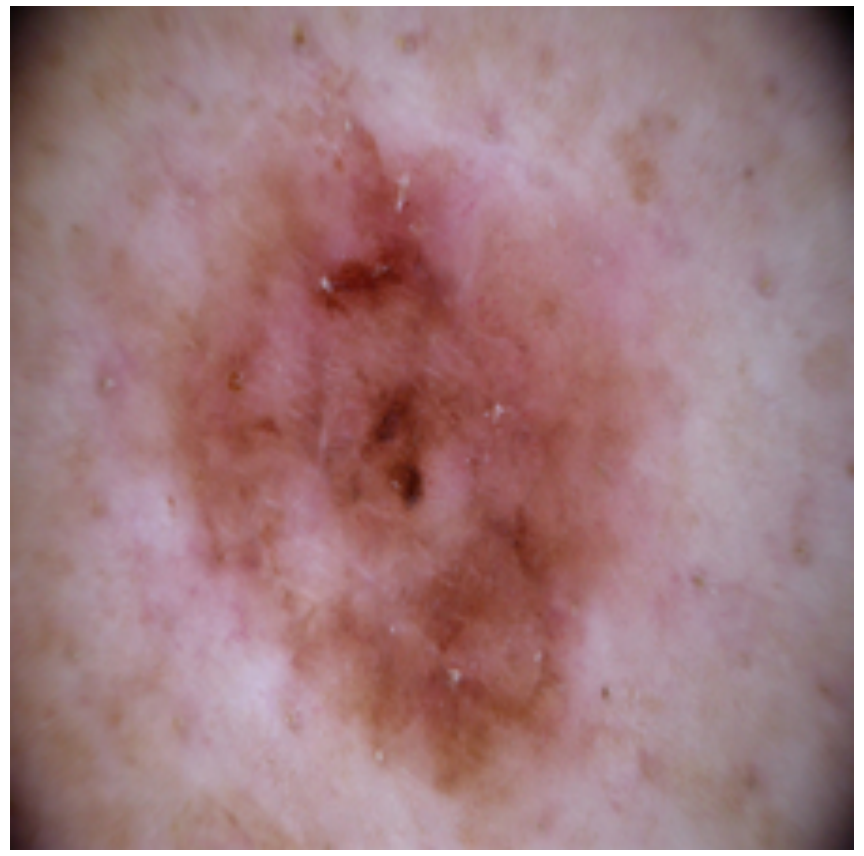
- **Total Images:** 3600.

- All images are of size 224x224 pixels, suitable for deep learning methods.

- **Purpose:** Provides high-quality dermoscopic images for training and evaluating skin cancer detection models.



Benign

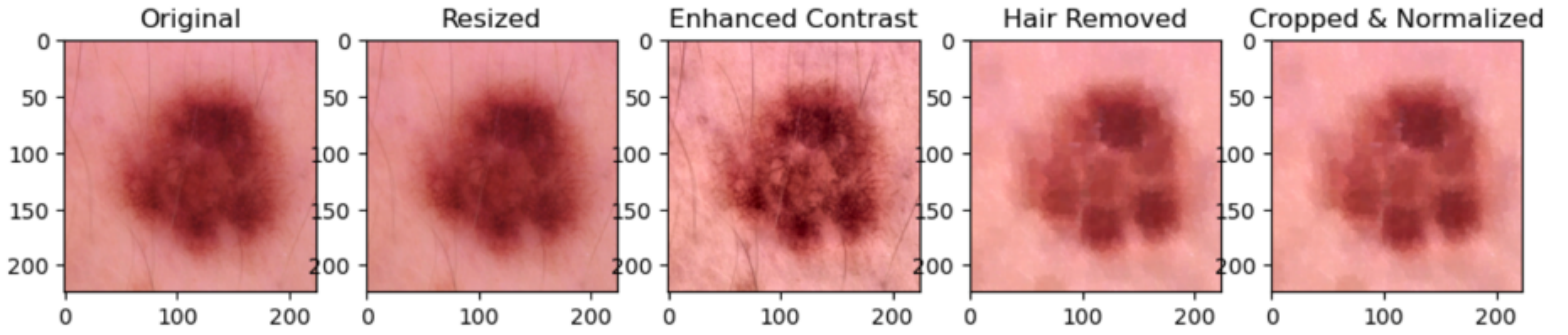


Malignant

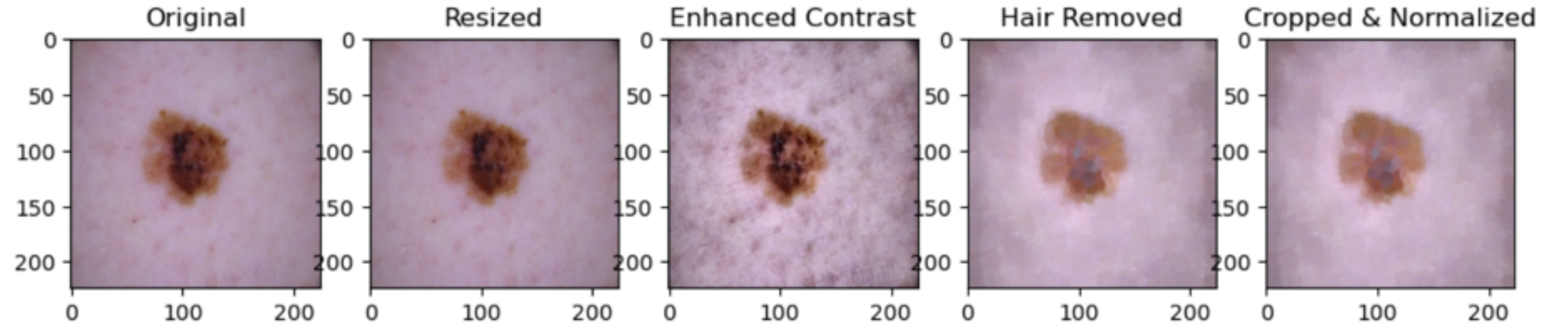
Image Processing

- Image Resizing: All training images are resized to 224x224 pixels to ensure consistent input dimensions for the model.
- Contrast Enhancement: **CLAHE** is applied to improve contrast, enhancing key features of skin lesions.
- Hair Removal: Hairs are removed using **Blackhat** Morphology and inpainting techniques.
- Lesion Cropping: Images are cropped to the lesion's bounding box to focus on the region of interest .
- Normalization: Pixel values are scaled to the range of [0, 1] for model compatibility and efficient training.

Image Processing



Benign



Malignant

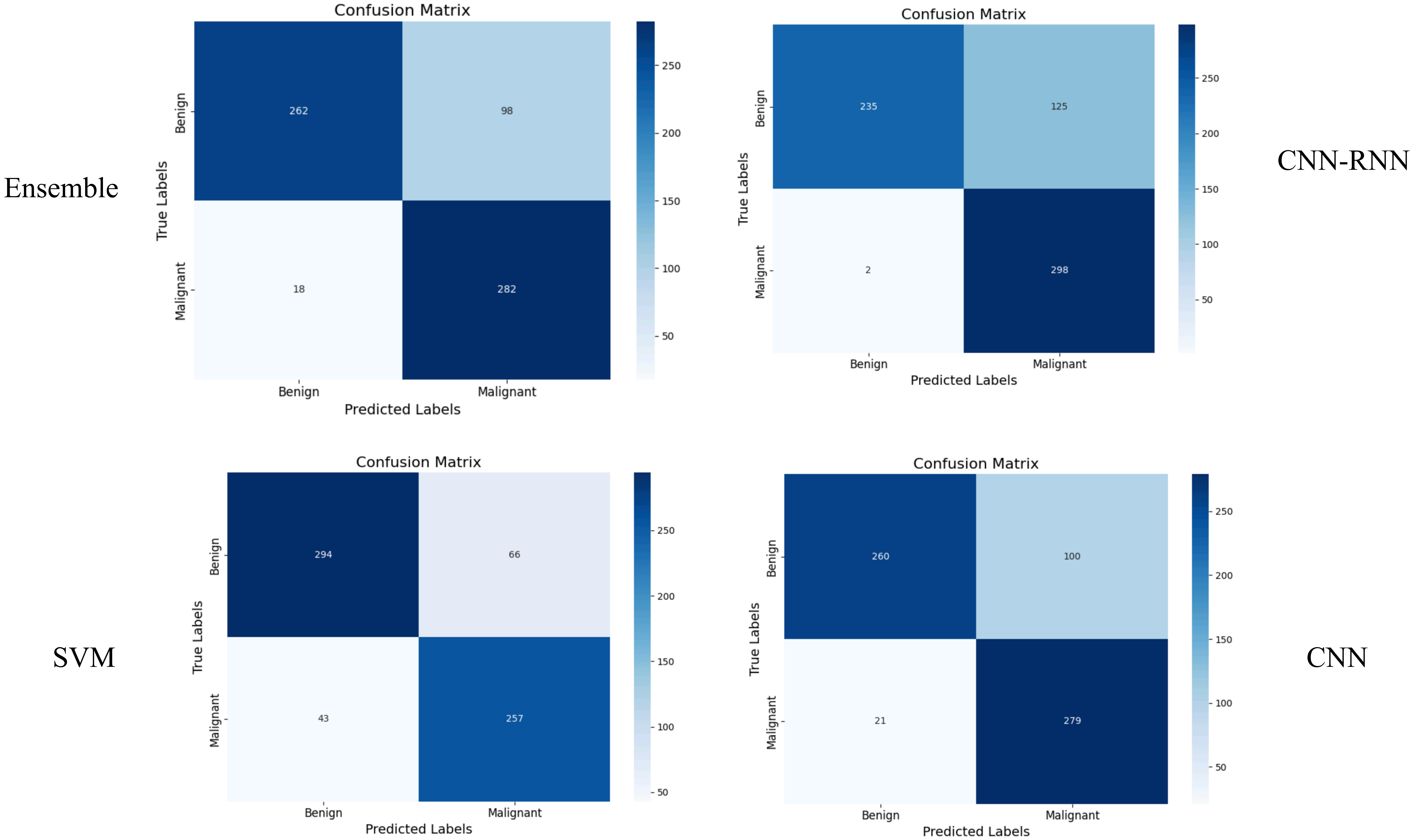
Deep Learning Models

Aspect	Simple CNN	Hybrid CNN-RNN	Ensemble Model	SVM Classifier
Architecture	Sequential CNN with Conv2D, MaxPooling, and Dense Layer	Combines CNN for feature extraction and LSTM for sequential learning	Weighted ensemble of Simple CNN and Hybrid CNN-RNN	Support Vector Machine with RBF Kernel
Model Type	Deep Learning	Deep Learning (Hybrid)	Ensemble Learning	Classical Machine Learning
Activation Functions	ReLU (Conv2D, Dense), Sigmoid (Output)	ReLU (Conv2D, LSTM), Sigmoid (Output)	Depends on pre-trained models (ReLU, Sigmoid)	Not applicable
Key Parameters	Conv2D: 32, 64, 128 filters; Dense: 128 neurons	Conv2D: 32, 64, 128, 256, 512 filters; LSTM: 128 units	Alpha (Weight for ensemble averaging): 0.9504	Regularization (C=1.0), RBF kernel
Preprocessing Needs	Standard image preprocessing	Requires reshaping for LSTM	Predictions from two models; requires preprocessing	Requires feature vector conversions from image data
Strengths	Lightweight and easy to train	Captured both spatial and sequential features	Combines strengths of two models for better accuracy	Works well with small datasets and high-dimensional data
Weaknesses	May not capture complex relationships	Computationally intensive	Requires pre-trained models	Loses spatial information due to feature flattening
Training Complexity	Low	Moderate to High	Depends on pre-trained models	Low

Performance Measures and Results

Models	Simple CNN	Hybrid CNN-RNN	Ensemble Model	SVM Classifier
Test Accuracy	81.67%	80.76%	82.42%	83.48%
Precision (B)	0.93	0.95	0.94	0.87
Precision (M)	0.74	0.72	0.74	0.80
Recall (B)	0.72	0.68	0.73	0.82
Recall (M)	0.93	0.96	0.94	0.86
f1-score (B)	0.81	0.79	0.82	0.84
f1-score (M)	0.82	0.82	0.83	0.83

- SVM Classifier achieves the highest test accuracy (83.48%), outperforming other models.
- Despite its complexity, the Hybrid CNN-RNN model has the lowest accuracy (80.76%).
- The EnsembleModel maintains a balance between precision, recall, and F1-score, with consistent performance across both classes
- Precision for the Benign class (B) is generally higher than Malignant (M) across all models, indicating better identification of Benign cases.
- The Hybrid CNN-RNN model has the highest recall (0.96) for Malignant cases.

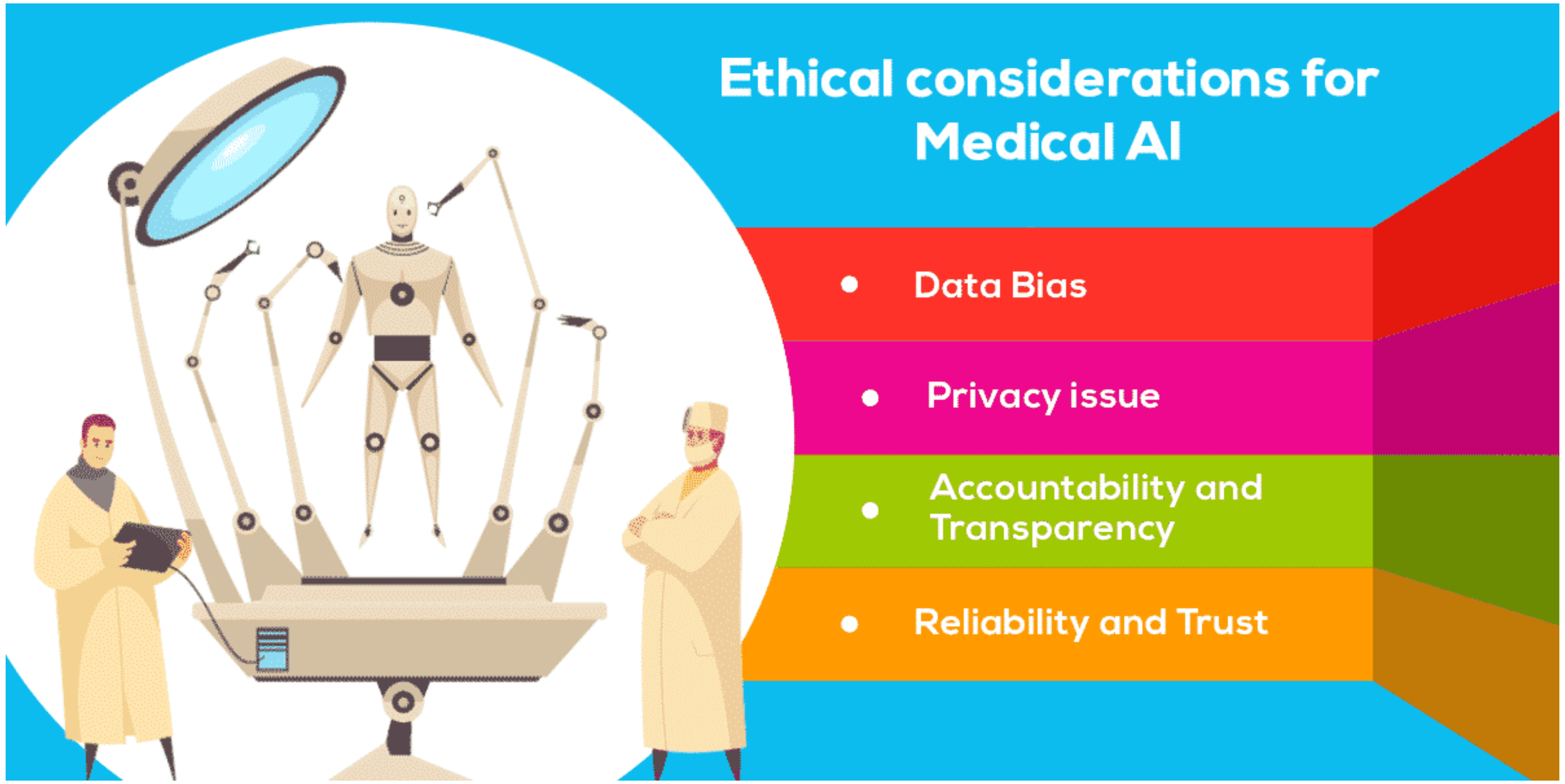

Ensemble
Confusion Matrix
True Labels
Benign
Malignant
262
98
18
282
Predicted Labels
CNN-RNN
Confusion Matrix
235
125
2
298
SVM
Confusion Matrix
294
66
43
257
CNN
Confusion Matrix
260
100
21
279

Challenges

- Datasets often have an unequal representation of benign and malignant cases, which can lead to biased model predictions.
- Presence of reflections, or imaging inconsistencies in dermoscopic images can affect model accuracy.
- High-quality, labeled datasets for medical images are scarce, which limits the generalizability of models.
- Explaining model decisions to clinicians is difficult, which can hinder trust and adoption in practice.
- Distinguishing subtle features between benign and malignant lesions can be challenging for models.
- Training deep learning models for, especially hybrid or ensemble architectures, requires substantial computational resources.
- Use of patient data for training models raises issues of privacy, consent, and bias in decision-making.

Discussions

- How well do the models generalize to unseen data?
- How does the preprocessing pipeline impact model accuracy?
- How does the choice of alpha affect the ensemble model's performance?
- Can these models handle larger datasets effectively, or are these bottlenecks in terms of training time and computational cost?
- How reliable are the models in real-world clinical settings?
- How can we ensure that the models are unbiased and protect patient data privacy?



Conclusions

- Deep learning models, particularly CNNs and hybrid architectures, demonstrate strong potential in accurately classifying skin lesions.
- Ensemble techniques improve robustness and accuracy by leveraging the strengths of multiple models.
- Effective preprocessing steps, such as hair removal and contrast enhancement, are crucial for improving model performance.
- Issues like data imbalance, limited datasets, and interpretability remain significant barriers to achieving reliable, real-world deployment.
- Incorporating explainable AI methods, expanding datasets, and addressing biases can enhance the applicability and trustworthiness of the models.
- While promising, combining technical advancements with ethical considerations is essential for responsible use of deep learning in healthcare.

Paper Summaries

	Paper Name	Applications	Research tasks	Dataset	Data processing	DL models	Performance measures and results
1	Enhanced skin cancer diagnosis using optimized CNN architecture and checkpoints for automated dermatological classification	Disease Diagnosis	Skin Cancer Detection	HAM10000	Image resizing, Normalization, Data augmentation	CNN	Accuracy: 97.858%
2	Detection of skin cancer based on skin lesion images using deep learning	Cancer, Skin Cancer	Disease detection	International Skin Imaging Collaboration (ISIC) 2018	Data augmentation, image improvement using (ESRGAN), image resizing, and normalization	CNN, ResNet50, InceptionV3, Inception ResNet	Accuracy CNN: 83.1% ResNet50: 83.6% InceptionV3: 85.7% Inception ResNet: 84.1%
3	Skin Cancer Classification using Deep Learning and Transfer Learning	Cancer	Skin Cancer Classification	ph2	Data augmentation	AlexNet	Accuracy: 98.61%
4	Skin cancer detection by deep learning and sound analysis algorithms: A prospective clinical study of an elementary dermoscope	Skin Cancer, Melanoma	Cancer detection	International Skin Imaging Collaboration (ISIC) 2017 800 non-dermoscopic regular photos	Image Augmentation, Sonification, FFT Analysis	CNN based on Inception V2 For audio data, 1D CNN	Sensitivity: 91.7% (for elementary device) Specificity: 41.8% (for elementary dermoscope)
5	Skin Cancer detection using combined decision of deep learners.	Cancer	Skin Cancer Detection	International Skin Imaging Collaboration (ISIC) 2019	Data Augmentation and Resizing, Image Preprocessing	VGG16, CapsNet, ResNet, Ensemble Model(combination of these 3)	Ensemble Model Accuracy: 93.5%
6	Skin cancer detection using convolutional neural networks.	Skin Cancer	Disease Classification	International Skin Imaging Collaboration (ISIC)	Image Preprocessing and Resizing, Data Augmentation, Normalization	VGG16	Accuracy: 87.6%
7	Skin cancer detection using ensemble of machine learning and deep learning techniques.	Melanoma, Cancer	Skin Cancer Detection	International Skin Imaging Collaboration (ISIC) Archive	Feature Extraction using ML models Data Augmentation using DL models	InceptionV3, VGG19, ResNet50, DenseNet201, InceptionResNetV2 ML models for Ensemble: Logistic Regression, Linear Support Vector Machine	Best performing model (VGG19) Accuracy: 93%
8	Skin Cancer Detection using Machine Learning and Deep Learning	Skin Cancer	Skin Cancer Detection	HAM10000	Image Preprocessing, Data Augmentation	VGG16 pre-trained on ImageNet	Accuracy: 95%

References

- Wu, Y., Chen, B., Zeng, A., Pan, D., Wang, R. and Zhao, S., 2022. Skin cancer classification with deep learning: a systematic review. *Frontiers in Oncology*, *12*, p.893972.

- Musthafa, M.M., TR, M., V, V.K. and Guluwadi, S., 2024. Enhanced skin cancer diagnosis using optimized CNN architecture and checkpoints for automated dermatological lesion classification. *BMC Medical Imaging*, *24*(1), p.201.

- Vidya, M. and Karki, M.V., 2020, July. Skin cancer detection using machine learning techniques. In 2020 IEEE international conference on electronics, computing and communication technologies (CONECCT) (pp. 1-5). IEEE.

- Tembhurne, J.V., Hebbar, N., Patil, H.Y. and Diwan, T., 2023. Skin cancer detection using ensemble of machine learning and deep learning techniques. *Multimedia Tools and Applications*, *82*(18), pp.27501-27524.

- Gangan, U., Manjula, V. and Rajasekaran, R.T., 2023, November. Skin Cancer Detection using Machine Learning and Deep Learning. In *2023 International Conference on System, Computation, Automation and Networking (ICSCAN)* (pp. 1-6). IEEE.

- Gouda, W., Sama, N.U., Al-Waakid, G., Humayun, M. and Jhanjhi, N.Z., 2022, June. Detection of skin cancer based on skin lesion images using deep learning. In *Healthcare* (Vol. 10, No. 7, p. 1183). MDPI.

- Daghrir, J., Tlig, L., Bouchouicha, M. and Sayadi, M., 2020, September. Melanoma skin cancer detection using deep learning and classical machine learning techniques: A hybrid approach. In *2020 5th international conference on advanced technologies for signal and image processing (ATSIP)* (pp. 1-5). IEEE.

- Dascalu, A. and David, E.O., 2019. Skin cancer detection by deep learning and sound analysis algorithms: A prospective clinical study of an elementary dermoscope. *EBioMedicine*, *43*, pp.107-113.

- Malo, D.C., Rahman, M.M., Mahbub, J. and Khan, M.M., 2022, January. Skin cancer detection using convolutional neural network. In *2022 IEEE 12th Annual Computing and Communication Workshop and Conference (CCWC)* (pp. 0169-0176). IEEE.

- Hosny, K.M., Kassem, M.A. and Foaud, M.M., 2018, December. Skin cancer classification using deep learning and transfer learning. In *2018 9th Cairo international biomedical engineering conference (CIBEC)* (pp. 90-93). IEEE.

- Imran, A., Nasir, A., Bilal, M., Sun, G., Alzahrani, A. and Almuhaimeed, A., 2022. Skin cancer detection using combined decision of deep learners. *IEEE Access*, *10*, pp.118198-118212.

Thank You