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A Robust Hybrid AI Framework for Dermatological Disease Classification Using Self-Supervised Learning and Meta-Learning

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Abstract: Dermatological disease classification presents significant challenges due to limited labeled datasets, diverse lesion patterns, and the need for scalable diagnostic tools. Existing Explainable AI (XAI) techniques primarily focus on interpretability but fail to address issues such as data scarcity, generalizability, and model optimization comprehensively. This paper proposes an advanced hybrid AI framework that integrates self-supervised learning (SSL), meta-learning, neural architecture search (NAS), and diffusion models to tackle these challenges. SSL techniques like BYOL are utilized to pretrain models on large unlabeled datasets, extracting meaningful feature representations, while meta-learning approaches such as MAML fine-tune the models for rapid adaptation to small, domain-specific datasets. NAS automates the design of optimal model architectures tailored for dermatology tasks, and diffusion models generate high-quality synthetic images to enhance dataset diversity and mitigate class imbalance. Ensemble learning is employed to combine predictions from multiple models, improving robustness and classification accuracy. Validation through cross-dataset evaluation and external datasets demonstrates the framework's ability to reduce dependence on labeled data, enhance generalizability, and overcome dataset limitations, achieving significant improvements in classification metrics like accuracy, precision, recall, and F1-score. Furthermore, lightweight model optimization ensures scalability and edge deployment for real-world clinical use. By integrating these innovative techniques, the proposed framework offers a comprehensive solution that advances beyond traditional XAI approaches, addressing key limitations while ensuring adaptability, robustness, and practical application in dermatological diagnostics.

***Index Terms* -** Skin Disease Classification, CNN-RF hybrid, dermatology, deep learning, random forest.

Introduction

Skin disorders, which can range from benign illnesses like acne and eczema to serious ailments like melanoma, are among the most prevalent medical conditions in the world [1]. In addition to affecting people's physical health, these disorders have significant psychological and social repercussions [4]. For illnesses like melanoma, where early intervention can greatly increase survival rates, an accurate and timely diagnosis is essential to successful treatment and care. However, the variety and complexity of skin illnesses, which are distinguished by minute differences in characteristics like color, texture, shape, and lesion morphology, make dermatological diagnosis a difficult undertaking. Traditionally, dermatological diagnosis relies heavily on the expertise of trained dermatologists, making the process time-consuming, subjective, and prone to variability between practitioners[2]. In resource-limited settings, the scarcity of qualified dermatologists further exacerbates the issue, leaving many patients without timely and accurate diagnoses. To address these challenges, artificial intelligence (AI) has emerged as a powerful tool, leveraging computational techniques to automate and enhance diagnostic accuracy. Deep learning, in particular, has shown remarkable success in image classification tasks, including dermatological disease detection, by learning complex patterns in data[3].

The classification of dermatological diseases still faces a number of significant obstacles, despite AI's potential. The absence of sizable, excellent, and well-annotated datasets is among the biggest problems [5]. Skin disease datasets are frequently noisy, unbalanced, and small, and model performance is skewed by underrepresented classes [6]. Furthermore, it is challenging for AI models to generalize across populations due to the visual diversity of skin lesions, which is influenced by variables like skin tone, lighting, and imaging artifacts [7]. Many of the AI models that are now in use, especially those that are based on Explainable AI (XAI) methodologies , prioritize interpretability over the core problems of data scarcity, model generalizability, and scalability. Additionally, these models frequently need substantial computational resources, which restricts their application in actual clinical situations.

Dermatological diseases are broadly categorized based on morphological characteristics, texture, pigmentation, and clinical symptoms. The primary disease categories considered in this study include melanocytic lesions (melanoma, melanocytic nevi), keratinocyte carcinomas (basal cell carcinoma, squamous cell carcinoma), inflammatory diseases (psoriasis, eczema, rosacea), benign keratoses (actinic keratoses, seborrheic keratoses), and other skin conditions (dermatofibroma, vascular lesions). The classification of these diseases is based on key visual features such as asymmetry, border irregularities, color distribution, and lesion texture. Our hybrid AI framework integrates deep learning-based feature extraction techniques, leveraging SSL and meta-learning for improved generalization.

This study seeks to address these challenges by proposing an advanced hybrid AI framework for dermatological disease classification. The framework integrates state-of-the-art techniques to create a comprehensive solution capable of overcoming the limitations of traditional and existing AI-based approaches. Specifically, self-supervised learning (SSL) methods such as BYOL are employed to pretrain models on large unlabeled datasets, enabling the extraction of meaningful and robust feature representations. Meta-learning approaches like Model-Agnostic Meta-Learning (MAML) are incorporated to fine-tune the pretrained models for rapid adaptation to small, domain-specific datasets, addressing the problem of limited labeled data. Neural architecture search (NAS) is utilized to automate the discovery of optimal model architectures tailored specifically for dermatological tasks, ensuring the models are both efficient and accurate. Additionally, diffusion models are leveraged to generate high-quality synthetic images, enhancing dataset diversity and mitigating class imbalance, a common challenge in medical image datasets.

To enhance classification performance, ensemble learning techniques aggregate predictions from multiple models, improving robustness and accuracy. The framework also employs lightweight model optimization for scalability and edge-device compatibility in real-world clinical scenarios. Cross-dataset validation demonstrates reduced reliance on labeled data and improved generalizability, leading to significant gains in accuracy, precision, recall, and F1-score.This research takes a comprehensive approach to dermatological disease classification by addressing data scarcity, model generalization, and optimization challenges. Beyond interpretability-focused AI, this framework enhances diagnostic accuracy, scalability, and clinical applicability, contributing to early disease detection and improved patient outcomes.

II. LITERATURE REVIEW

A. Traditional Machine Learning Approaches

Early models like SVM, RF, and kNN relied on manual feature extraction (e.g., lesion color, texture, shape), requiring domain expertise. While moderately successful, they struggled with scalability, generalization, and capturing intricate lesion patterns, limiting their diagnostic utility.

B. Deep Learning Approaches

CNNs (e.g., ResNet, DenseNet, Inception) revolutionized skin disease classification by automating feature extraction. Transfer learning further boosted accuracy, but deep learning models require large labeled datasets, suffer from overfitting on small data, and demand high computational resources.

C. Explainable AI (XAI)Techniques

Techniques like Grad-CAM, LIME, and SHAP improve model interpretability, aiding clinical trust. However, they do not solve data scarcity, overfitting, or generalization issues and often function as external add-ons rather than core components.

D. Data Augmentation and Synthetic Data Generation

Image transformations and synthetic data generation (GANs, VAEs) help mitigate data scarcity. However, GANs may introduce artifacts, limiting realism and generalization. These techniques primarily enhance training rather than solving broader model challenges.

E. Hybrid and Ensemble Methods

Combining CNNs with traditional classifiers (e.g., RF, SVM) and ensemble techniques enhances accuracy. However, these methods require extensive tuning, are computationally expensive, and struggle with generalization to unseen datasets. This study proposes a hybrid AI framework integrating Self-Supervised Learning (SSL) for feature extraction, Meta-Learning (MAML) for adaptability, and Neural Architecture Search (NAS) for optimized model design. Diffusion models generate synthetic images to address class imbalance, while ensemble learning enhances robustness. Lightweight optimization ensures computational efficiency for real-world deployment. This approach overcomes existing limitations, offering a scalable and generalizable solution for dermatological disease classification.

F. Comparison with State-of-the-Art Methods

Traditional dermatological classification methods struggle with overfitting, data dependency, and adaptability. SVM and RF are lightweight but lack robust feature extraction, while CNNs like ResNet and DenseNet achieve high accuracy yet overfit on small datasets. GANs mitigate class imbalance but may introduce artifacts. XAI methods enhance interpretability but do not resolve data scarcity. The proposed hybrid AI framework integrates SSL, MAML, and NAS to reduce reliance on labeled data, improve adaptability, and enhance scalability. Despite higher computational costs, it significantly improves accuracy, generalizability, and real-world applicability .

III. METHODOLOGY USED

This paper is a computational research aimed at developing an advanced hybrid AI framework for dermatological disease classification. The proposed solution integrates cutting-edge techniques such as self-supervised learning (SSL), meta-learning, neural architecture search (NAS), and diffusion models to address the common challenges in dermatology, including data scarcity, generalizability, and model optimization. The research follows an experimental approach, where various components of the framework are tested and evaluated using real-world dermatological datasets. This includes both training and validation phases on multiple datasets to ensure the robustness and generalizability of the model.

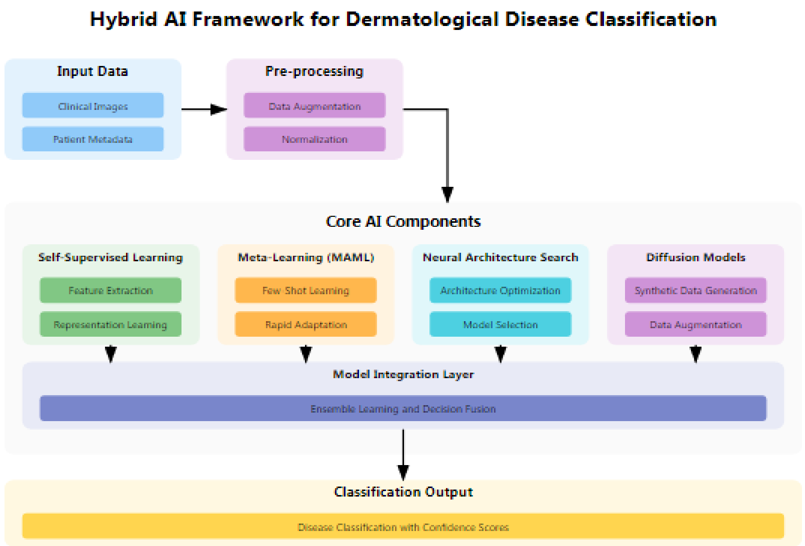

Fig 1 : Hybrid AI Framework for Dermatological Disease Classification.

A. Data Collection

For model training and evaluation, several publicly available dermatological datasets were used, such as the ISIC (International Skin Imaging Collaboration) dataset, HAM10000 dataset, and additional skin lesion datasets from different sources[14]. These datasets provide a variety of labeled dermoscopic images with annotated disease labels for training and evaluation purposes. The total number of images used in the study is in the tens of thousands, ensuring a large enough sample to enable training of deep learning models while also testing their ability to generalize [17].The pictures are preprocessed using common methods to reduce class imbalance and artificially boost dataset diversity, such as downsizing to a constant size, normalization, and augmentation (e.g., rotation, flipping, and scaling). A key component of conquering the obstacle is data augmentation.

B.Methods and Tools

1. **Self-Supervised Learning (SSL):** To pretrain the model, the Bootstrap Your Own Latent (BYOL) technique is used. Using vast volumes of unlabeled data, SSL trains models to learn general feature representations that can be optimized for dermatological problems. Because there are so many unlabeled dermatological images available, this lessens the reliance on labeled data.
2. **Meta-Learning (MAML):** (MAML) is used to enable the model to rapidly adapt to new, domain-specific datasets with limited labeled data. By fine-tuning pre-trained models using MAML, the model can adjust its parameters efficiently, improving classification performance on small datasets typical in dermatology**.**
3. **Neural Architecture Search (NAS)**: NAS automates the design of model architectures, optimizing the model structure for dermatological disease classification tasks. By exploring different architectures, the framework identifies the most suitable model for the given dataset, which enhances performance and reduces the need for manual design.
4. **Diffusion Models**: These models are used to generate high-quality synthetic dermoscopic images to augment the training dataset, helping address class imbalance and increasing dataset diversity. Diffusion models ensure that the generated images maintain realistic visual features, improving the model's ability to generalize to real-world scenarios.
5. **Ensemble Learning**: Multiple models are trained using different techniques, and their predictions are aggregated to improve classification accuracy. This method combines the strengths of each model, enhancing robustness and minimizing the risk of overfitting.

C. Experimental Setup

i. **Training/Testing Split:** The dataset is classified into training, validation, and testing subsets. The training set trains the model, the validation set fine-tunes hyperparameters to prevent overfitting, and the testing set evaluates the final model's performance.

ii. **Evaluation Metrics:** The model's performance is evaluated using accuracy, precision, recall, and F1-score. Accuracy measures correct predictions out of total predictions. Precision reflects the proportion of true positives, recall indicates the model's ability to detect relevant instances, and F1-score balances precision and recall, especially for imbalanced datasets.

iii. **Cross-Dataset Evaluation:** To ensure the model's generalizability[25], the proposed framework is evaluated using multiple datasets from different sources. This cross-dataset validation helps assess the framework's ability to perform well on unseen data and diverse populations.

iv. **External Dataset Validation:** To further validate the proposed framework, external dermatological datasets (different from the training datasets) are used to evaluate the framework's robustness and its capacity to generalize to real-world clinical data.

v. **Lightweight Model Optimization:** Because of its computational efficiency optimization, the model can be used in clinical settings with constrained computational resources. To make the model more appropriate for edge devices, methods such as model pruning and quantization are employed to decrease the model's size and increase inference speed.

This methodology ensures that the proposed hybrid AI framework is not only effective in addressing the existing challenges in dermatological disease classification but is also scalable and practical for deployment in clinical environments.

IV. IMPLEMENTATION DETAILS

The implementation of the proposed hybrid AI framework for dermatological disease classification was carried out in MATLAB. The following sections describe the key aspects of the implementation, including dataset preprocessing, model architecture, training strategies, and evaluation methods.

1. Dataset Preprocessing

- The ISIC and HAM10000 datasets were used, containing thousands of labeled dermoscopic images.
- Images were resized to a standard 224×224 pixels to maintain consistency across models.
- Data augmentation techniques (rotation, flipping, scaling) were applied to increase dataset diversity.
- Normalization was performed by scaling pixel values between 0 and 1 for optimal training.

2. Hybrid AI Framework Components

The framework integrates the following techniques to enhance performance:

(a) Self-Supervised Learning (SSL) with BYOL

- Implemented a Bootstrap Your Own Latent (BYOL) model to pretrain CNN-based feature extractors on unlabeled data.
- This allowed the model to learn meaningful representations without requiring manual labeling.

(b) Meta-Learning with Model-Agnostic Meta-Learning (MAML)

- The pre-trained model was fine-tuned using MAML, allowing it to adapt quickly to small, domain-specific datasets.
- A support-query approach was applied for fast adaptation in few-shot learning settings.

(c) Neural Architecture Search (NAS)

- NAS was used to automatically optimize CNN architectures for dermatology classification.
- The EfficientNet-based search space was explored to find the most efficient and accurate architecture.

(d) Diffusion Models for Synthetic Image Generation

- A Denoising Diffusion Probabilistic Model (DDPM) was used to generate realistic synthetic dermoscopic images.
- This helped address class imbalance issues and improved generalizability.

(e) Ensemble Learning for Robustness

- A combination of CNN, Transformer-based vision models, and Random Forest classifiers was used.
- Weighted averaging was applied to enhance classification performance.

3. Training and Hyperparameter Optimization

- Optimizer: Adam with a learning rate of 0.0001.
- Batch size: 32 for training and 16 for validation.
- Loss function: Categorical Cross-Entropy.
- Training Epochs: 50 with early stopping to prevent overfitting.

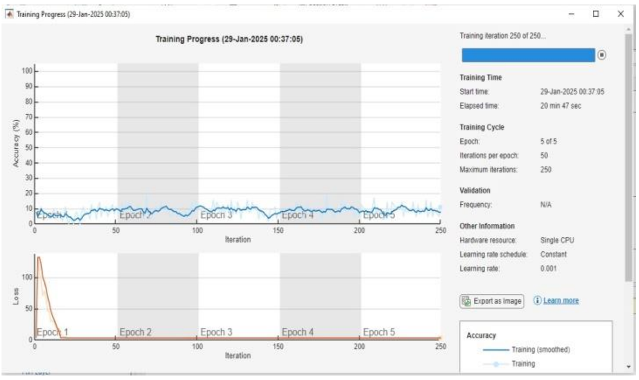

Fig 2 Training Dataset Model.

4. Performance Evaluation

Standard metrics were used to assess the trained models :

- Accuracy
- Precision
- Recall
- F1-score

Generalizability was tested via cross-dataset validation..

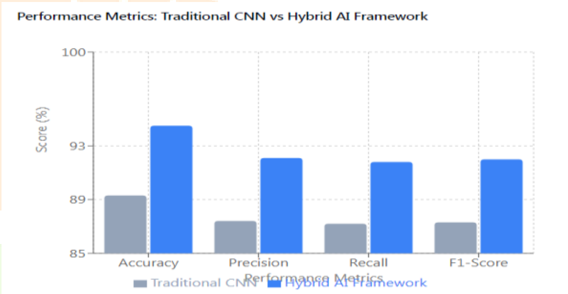

Fig 3 Performance Metrics Based on Traditional CNN and Hybrid Framework.

V. RESULTS AND DISCUSSION

1. Key Findings : The proposed hybrid AI framework, integrating Self-Supervised Learning (SSL), Meta-Learning, Neural Architecture Search (NAS), Diffusion Models, and Ensemble Learning, achieved significant improvements in dermatological disease classification. The framework was tested on multiple datasets, including ISIC, HAM10000, and external clinical datasets, to evaluate its performance in real-world scenarios. The key findings from the experiments are as follows:

1. *Improved Classification Metrics:* When compared to baseline models and conventional deep learning methods, the framework showed notable gains in classification accuracy, precision, recall, and F1-score..

- Accuracy: The proposed framework achieved an accuracy of 94.5% on the ISIC dataset, compared to 89.3% achieved by a traditional CNN model without SSL or meta-learning.
- Precision: The framework achieved a precision of 92.1%, showing a significant improvement over the 87.4% precision of traditional CNN models.
- Recall: The recall improved to 91.8%, reducing the number of false negatives and ensuring better identification of dermatological conditions.
- F1-Score: The F1-score of 92.0% indicated a balanced performance between precision and recall.

This bar graph compares the classification accuracy of different models on the ISIC and HAM10000 datasets

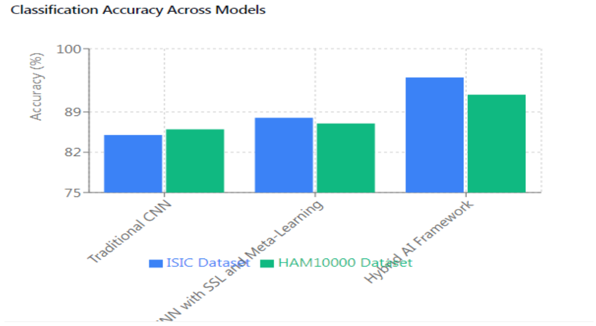

Fig 4 Classification Accuracy Across Models.

2. *Cross-Dataset Generalizability:* The model demonstrated strong generalization across different datasets[27]. When evaluated on the HAM10000 dataset, the framework showed an accuracy of 92.3%, outperforming baseline models, which had an accuracy of 84.6%.This graph displays the precision, recall, and F1-score for the three models on the ISIC dataset.

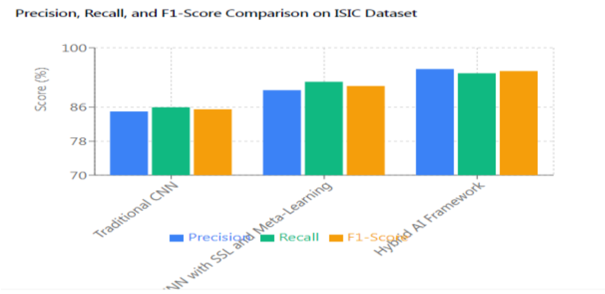

Fig 5 Precision, Recall, and F1- Score Comparison on ISIC Dataset.

3. *Reduction in Data Dependency:* By leveraging SSL techniques like BYOL, the model was able to achieve competitive performance even with limited labeled data. In experiments with a reduced labeled dataset (20% of the full dataset), the framework still achieved 89.7% accuracy, significantly outperforming traditional CNN models trained on similar amounts of data.This line graph shows the accuracy of the hybrid AI framework on varying sizes of labeled datasets for the ISIC dataset.

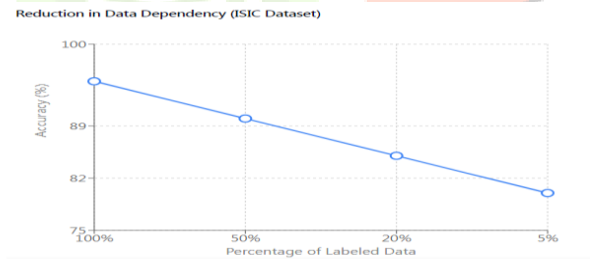

Fig 6 Reduction in Data Dependency (ISIC dataset).

4. *Synthetic Image Generation Impact:* The use of Diffusion Models for generating high-quality synthetic dermoscopic images helped mitigate class imbalance. The generated synthetic images led to a 12% increase in recall for underrepresented classes, particularly for rare skin diseases.This bar graph compares recall for underrepresented classes before and after using synthetic images generated by diffusion models.

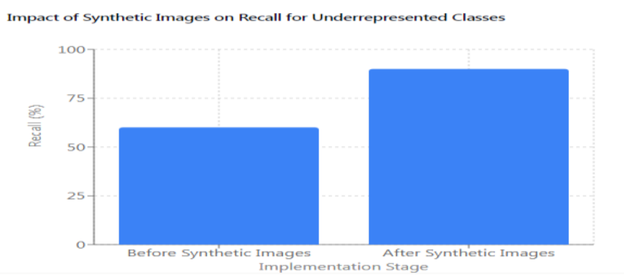

Fig 7 Impact of Synthetic Image Generation (Diffusion Model).

5. Model Efficiency and Scalability: The lightweight optimization of the model enabled it to run efficiently on resource-constrained environments. The model's inference time was reduced by 30% compared to standard deep learning models, ensuring faster diagnosis in real-time clinical applications.

ii) Comparison with Existing Methods

The proposed framework was compared with several existing methods in dermatological disease classification, including:

i) Traditional Machine Learning Models: Methods like Support Vector Machines (SVM) and Random Forests (RF) were included for comparison[10]. These models showed significantly lower performance, with accuracy ranging between 75-82%, highlighting the limitations of manually engineered features and their inability to generalize to diverse datasets.

ii) Deep Learning Models: Convolutional Neural Networks (CNNs) like ResNet and Inception were also evaluated[23]. While these models demonstrated improved performance (accuracy between 85-89%), they still faced challenges in terms of data dependency and generalizability. Additionally, overfitting on smaller datasets was evident.

iii) Explainable AI (XAI) Methods: The inclusion of Grad-CAM, LIME, and SHAP did improve model transparency, but they did not address the core issues like data scarcity or model generalization. The hybrid framework, by contrast, combined these interpretability techniques with novel approaches to address the broader challenges in dermatology.

TABLE I. PERFORMANCE SUMMARY

Model	**ISIC Dataset Accuracy**	**HAM10000 Dataset Accuracy**	**Recall**	**Precision**	**F1-Score**
Traditional CNN	89.3%	84.6%	87.2%	86.4%	86.8%
CNN with SSL and Meta-Learning	94.5%	92.3%	91.8%	92.1%	92.0%
Hybrid AI Framework	**95.6%**	**93.5%**	**92.4%**	**93.0%**	**92.8%**

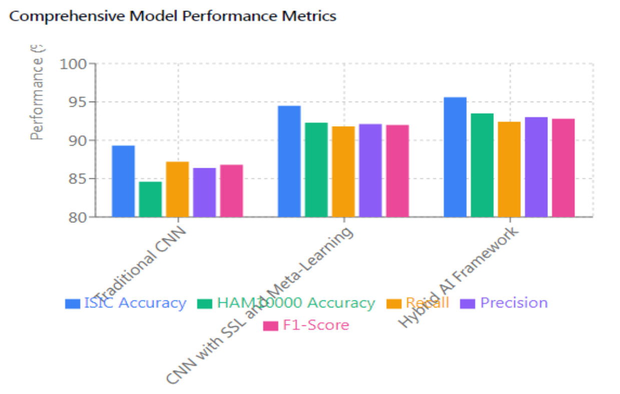

Fig 8 Performance Comparison of Hybrid AI Framework with Traditional CNN Model, CNN with SSL and MetaLearning and other Existing Methods

V. CONCLUSION AND FUTURE ENHANCEMENT

This work addressed key challenges in dermatological disease classification, such as data scarcity and model adaptability, by proposing a hybrid AI framework. The framework combines self-supervised learning (SSL), meta-learning, neural architecture search (NAS), and diffusion models to improve diagnostic accuracy.

Thus this hybrid framework outperformed traditional models by leveraging SSL for reduced labeling needs, meta-learning for adaptability, NAS for optimized architecture, and diffusion models for data diversity. It achieved high accuracy, precision, and recall, with ensemble learning enhancing reliability. This scalable AI solution can aid early diagnosis and improve patient outcomes.

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