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Detection of infectious skin diseases in children's nurseries using AI model

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Abstract. Infectious skin diseases present a significant health concern in children, particularly in densely populated environments such as nurseries. Early diagnosis is critical to preventing complications and improving healthcare outcomes. This study develops an image-based artificial intelligence (AI) model using the Mpox Skin Lesion Dataset v2.0 to detect infectious conditions such as measles, chickenpox, and hand-foot-mouth disease. Three convolutional neural network (CNN) architectures—ResNet50, VGG19, and a custom CNN—were trained and evaluated. The custom CNN achieved the highest validation accuracy at 88.70%, while VGG19 demonstrated superior generalization performance with an accuracy of 83.33% on unseen real-world clinical images. ResNet50 exhibited overfitting, underscoring the importance of selecting appropriate transfer learning strategies. The proposed system does not aim to replace healthcare professionals but rather to serve as a supportive diagnostic tool in pediatric and nursery settings. These findings suggest AI models can significantly enhance early screening processes and improve children's health outcomes.
Keywords: Pediatric skin disease detection, Deep learning, Transfer learning, VGG19, CNN, Streamlit deployment, Clinical image analysis.

1. Introduction

Skin is the largest organ of the body. It provides protection, controls body temperature and fluids, and allows perception of the outside world [1]. Newborns, kids, and teenagers can all be afflicted by a number of infectious skin conditions and infections [2], as the skin disease is the fourth most common cause of non-fatal disease burden worldwide, according to the Global Burden of Disease Project [3]. In children, whose immune systems are still developing, skin diseases, particularly infectious diseases pose a major health concern. In Africa, skin diseases are thought to affect between 21% and 87% of

children [4]. According to the WHO, melanoma, a type of cancer, affects about 132,000 people annually worldwide, while non-melanoma affects over 2 million people. Accordingly, not all skin conditions are malignant (melanomas) [5][6]; however, certain skin conditions can also arise because of other long-term illnesses. Approximately 75% of people with skin cancer die each year. If skin cancer is detected early, corrective action can be taken to eradicate the disease entirely from the body before it spreads to the skin and becomes incurable. These factors highlight the importance of an image-based detection system, which is reliable and accelerates the process of identifying skin diseases in children in crowded places such as nurseries. In this study, we propose an image-based model that uses artificial intelligence (AI) to identify skin diseases, which contributes to early identification of these diseases and thus improves safety and general health for children.

2. Materials and Methods

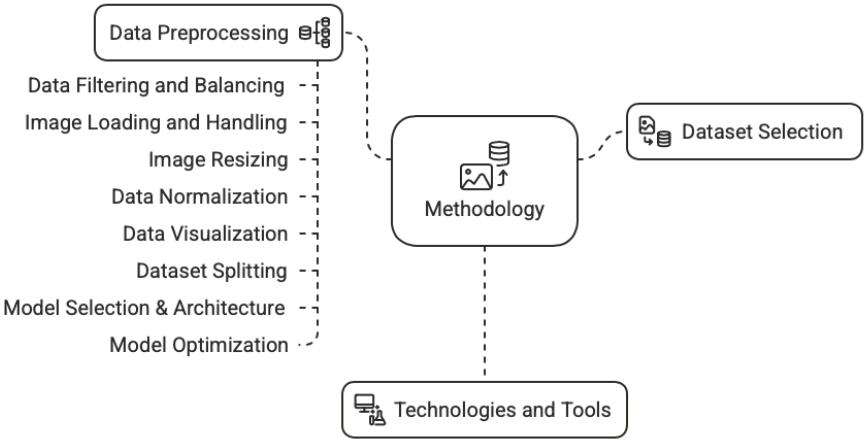


Figure 1. Methodology Pipeline for Image-Based Skin Disease Detection.

2.1. Dataset Selection

To classify infectious skin diseases in children, we used a dataset based on the Mpox Skin Lesion Dataset (MSLD) Figure 3, specifically the updated MSLD v2.0. [7]. Developed between June 2022 and May 2023, MSLD v2.0 expanded from a two-class system ("Mpox" and "Others" which included chickenpox and measles) into a more comprehensive six-class dataset. MSLD v2.0 consists of 755 original skin lesion images from 541 patients across six classes: Mpox (284), Chickenpox (75), Measles (55), Cowpox (66), Hand-foot-mouth disease (HFMD) (161), and Healthy (114). Figure 2 The MSLD v2.0 dataset has 5 folders, each with three sub-files, namely the training set, validation set, and test set. Moreover, the data folder “Augmented Images” contain enhanced versions of training images using techniques such as rotation, translation, reflection, shear, hue, saturation, contrast and brightness jitter, noise, scaling, etc. This latest version is endorsed by dermatologists and approved by regulatory authorities. and vascular lesions.

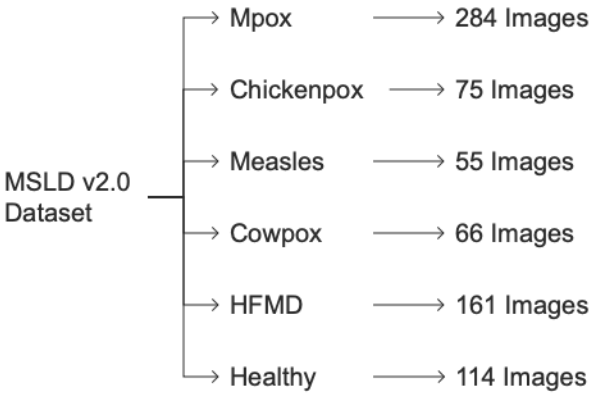


Figure 2. MSLD v2.0 Dataset Composition.

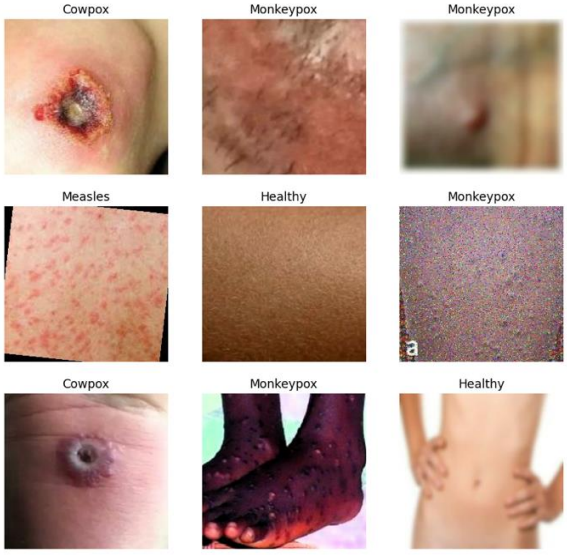


Figure 3. Sample of MSLD dataset.

2.2. Data Preprocessing

To ensure effective model training, a series of preprocessing steps were applied to the image dataset using Python with OpenCV and NumPy. The data was filtered to retain only measles, chickenpox, and hand-foot-and-mouth disease (HFMD) images, with each class capped at 532 samples for balance. A fourth "unknown" class was introduced to encompass Monkeypox, Cowpox, and Healthy cases for broader generalization. All images were loaded from file paths with error handling, converted from BGR to RGB, resized uniformly to 224×224 pixels, and normalized to a [0, 1] scale. The dataset was then split into training and validation sets using an 80/20 ratio, with prefetching enabled to accelerate data loading and maximize GPU performance. Figure 4 Visual inspections were conducted at different preprocessing stages to verify the transformations.

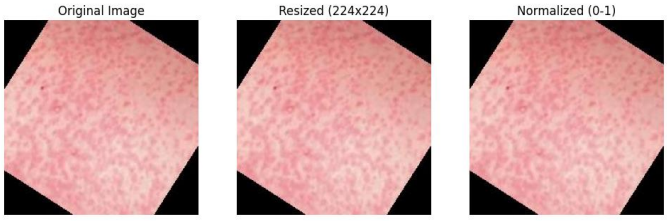


Figure 4. DataFrame after preprocessing.

2.3. Model Selection & Architecture

In this study, three convolutional neural network (CNN) architectures were developed and evaluated for the classification of skin conditions into four categories: measles, chickenpox, HFMD, and an "unknown" class comprising Monkeypox, Cowpox, and Healthy cases. The models included a custom-designed CNN developed from scratch, and two transfer learning architectures—ResNet50 and VGG19—pre-trained on the ImageNet dataset. The custom CNN architecture consisted of three convolutional blocks with increasing filter sizes (32, 64, 128), each followed by max-pooling and batch normalization layers. The classification head included flattening, fully connected layers, and dropout regularization to minimize overfitting. In contrast, the ResNet50 and VGG19 models leveraged the strength of transfer learning by retaining their pre-trained convolutional bases and appending new task-specific fully connected layers. These layers incorporated global average pooling, a dense layer with 512 units using ReLU activation, batch normalization, dropout (rate = 0.5), and a final softmax output layer comprising four neurons.

All models were trained using the Adam optimizer and categorical cross-entropy loss. The VGG19 architecture employed additional optimization strategies including early stopping and learning rate reduction to improve training efficiency and generalization. Evaluation results demonstrated that the custom CNN achieved a validation accuracy of 88.70% with a validation loss of 0.4089. The VGG19-based model achieved superior performance, reaching 98% validation accuracy with a notably low validation loss of 0.052. In contrast, the ResNet50 model exhibited severe overfitting, with a validation accuracy of just 0.24% and a significantly higher validation loss of 9.97. These outcomes underscore the importance of tailored architecture design and careful transfer learning adaptation when addressing domain-specific classification tasks.

2.4. Model Training and Optimization

Robust model training procedures were applied to enhance classification performance and generalization. All architectures were trained with categorical cross-entropy loss and optimized using the Adam optimizer. Cross-validation was conducted to mitigate overfitting and assess generalizability across different data splits. Additionally, learning rate scheduling and early stopping were employed to promote efficient convergence and control model complexity during training. The ResNet50 model, trained with frozen convolutional layers, reached 69% training accuracy but exhibited poor generalization on the validation set. In comparison, the custom CNN benefited from early stopping with a patience parameter of 5 and ReduceLROnPlateau callbacks, achieving 88% validation accuracy. Two variants of the VGG19 architecture were implemented to further optimize performance. In the first variant, the convolutional base remained entirely frozen, allowing only the newly added top layers to be trainable. This configuration yielded strong results with 98% validation accuracy and a validation loss of 0.0523. The second variant employed partial fine-tuning, unfreezing the last five

convolutional layers and adjusting the learning rate to 1e-4 to facilitate stable gradient updates. The early stopping callback was further refined by introducing a min_delta value of 0.02 to enforce more stringent improvement criteria. This approach demonstrated enhanced learning dynamics, particularly in terms of convergence rate and validation accuracy, validating the effectiveness of controlled layer unfreezing in transfer learning scenarios.

2.5. Evaluation Metrics

The developed models were evaluated using a blend of statistical performance metrics and real-world clinical validation. Accuracy was the main criterion for measuring how effectively the models performed. Complementary metrics such as Precision, Recall, and F1-Score were also used to provide a well-rounded analysis. In addition to numerical assessment, the models were validated on actual clinical cases. This involved analyzing diagnostic images and patient records, with continuous collaboration from experienced medical professionals. Their expertise ensured that the models were clinically relevant, accurate, and applicable in practical settings. This combined approach offers technical reliability and practical applicability in pediatric healthcare settings.

2.6. System Implementation and Deployment

Figure 5, The development and deployment of the skin disease classification system followed a systematic pipeline consisting of the following stages:

1. Local Development and Testing;

The initial model and interface were implemented using Streamlit and tested locally to verify correct functionality and user interaction flow.

2. Version Control with GitHub;

The complete source code, including preprocessing scripts, model architecture, and the interface, was pushed to a GitHub repository to facilitate collaborative development and ensure proper versioning.

3. Deployment on Streamlit Cloud;

The application was deployed on Streamlit Cloud for public access. Two primary challenges were addressed during this step:

- Model Size Constraint;

The deep learning model exceeded the size limit for direct upload. To overcome this, the model was hosted on Google Drive and loaded into the application via a temporary file during runtime.

- Credential Security.

Since Google API keys cannot be exposed publicly, they were securely stored in the secrets.toml file, supported by Streamlit Cloud's secret management system.

4. Post-Prediction Data Logging.

After each prediction, the following information was recorded:

- Input image;
- Timestamp;
- Predicted disease class;
- Confidence score.

These entries were logged into a structured database using either Google Sheets or Google Drive, supporting future evaluation, performance auditing, and statistical analysis. Figure 7.

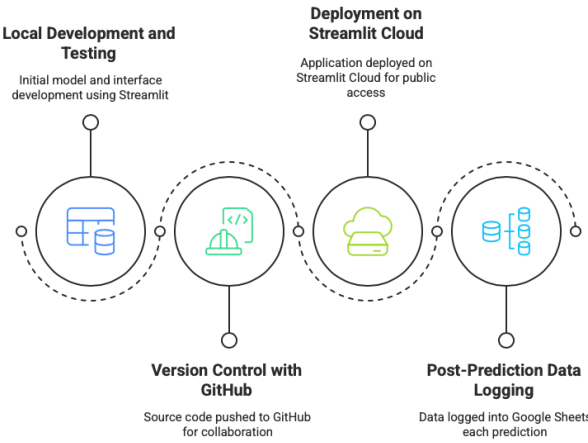
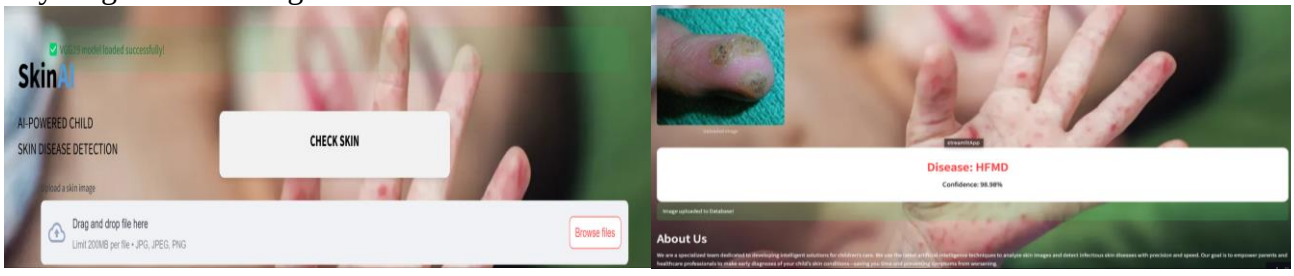


Figure 5. Skin Disease Classification System Implementation.

2.6.1. Skin AI Detection System Overview

The finalized deployment output of the classification pipeline is a web-based skin disease detection tool, developed using the Streamlit framework, designed to detect common childhood skin diseases—specifically chickenpox, hand-foot-and-mouth disease (HFMD), and measles— based on skin images that users can either upload from their device or capture in real-time using a camera Figure 5.a. The model backend utilizes a fine-tuned VGG19 convolutional neural network, trained to classify images into one of four categories: chickenpox, hfmd, measles, or unknown. The application includes a visually appealing interface, image preprocessing pipeline (resizing, normalization), and real-time prediction display with confidence scores Figure 5.b. This tool aims to serve as a preliminary screening aid, particularly in pediatric and telemedicine contexts, where quick visual assessments can support early diagnosis and triage.



(**a**) (**b**)

Figure 6. Skin AI Detection System Interface: (**a**) Sample of upload of the application; (**b**) Sample of output of the application.

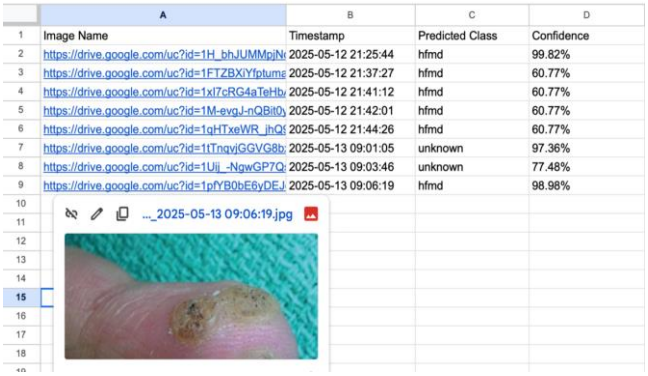


Figure 7. System database.

3. Results

3.1. Model Training Performance

Our proposed models used ResNet50, Custom CNN, and VGG19 models on the skin disease classification task were evaluated based on accuracy and loss metrics obtained from the validation dataset as mentioned in Table 1.

Table 1. Models Training Performance Comparison.

Model	Training Accuracy (%)	Training Loss	Validation Accuracy (%)	Validation Loss
ResNet50	0.69	0.78	0.24	9.9711
CNN	0.86	0.632	0.88	0.4089
VGG19 (1)	0.81	0.467	0.86	0.3947
VGG19 (2)	0.97	0.0757	0.98	0.0523

In Figure 8, Our ResNet50 model exhibited a substantial gap between training accuracy (69.30%) and validation accuracy (24.28%), along with a high validation loss (9.9711), indicating significant overfitting despite having its pre-trained layers frozen. This suggests that the frozen layers may not be well-suited to the specific nuances of the skin disease dataset.

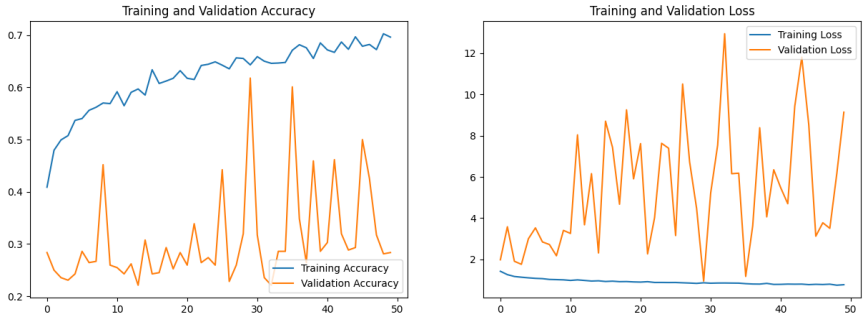


Figure 8. ResNet50 Training Curve.

Our Custom CNN model demonstrated exceptional performance, achieving a high validation accuracy of 88.70% and a low validation loss of 0.4089. This indicates that the model architecture is well-suited to the task, and the training process, incorporating early stopping and learning rate reduction, effectively prevented overfitting as shown in Figure 9. The last VGG19(2) model achieved a validation accuracy of 98.32% and a validation loss of 0.0523, signifying good generalization performance in Figure 10. The close proximity between training and validation accuracy suggests that transfer learning was successfully employed, leveraging pre-existing knowledge while adapting to the specific characteristics of the skin disease dataset.

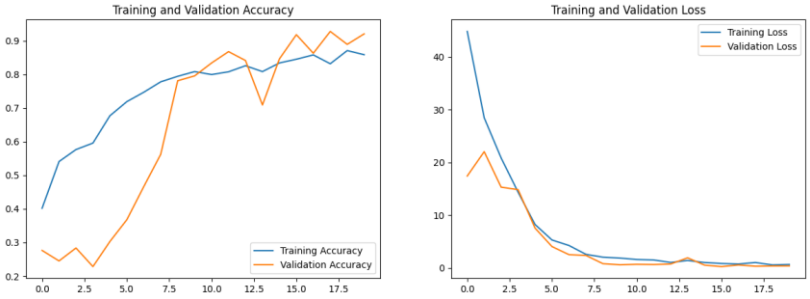


Figure 9. CNN Training Curve

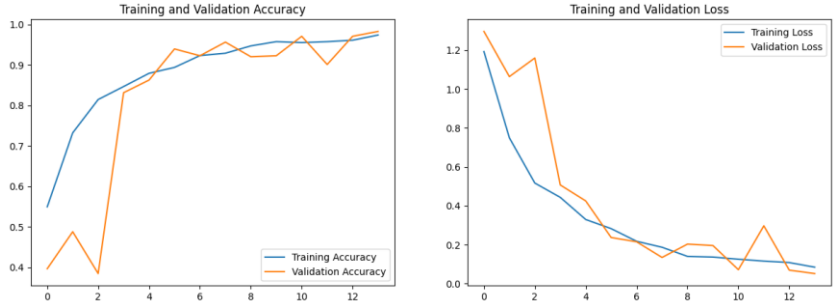


Figure 10. VGG-19 Training Curve.

3.2. Real-World Evaluation

Real-world testing was conducted using a folder containing 48 images containing chickenpox, hand, foot, mouth disease (HFMD), and measles classes. Figure 11 shows the VGG19 model's predictions

for diseases, along with the corresponding confidence scores for each prediction and with evaluation results shown in Table 2.

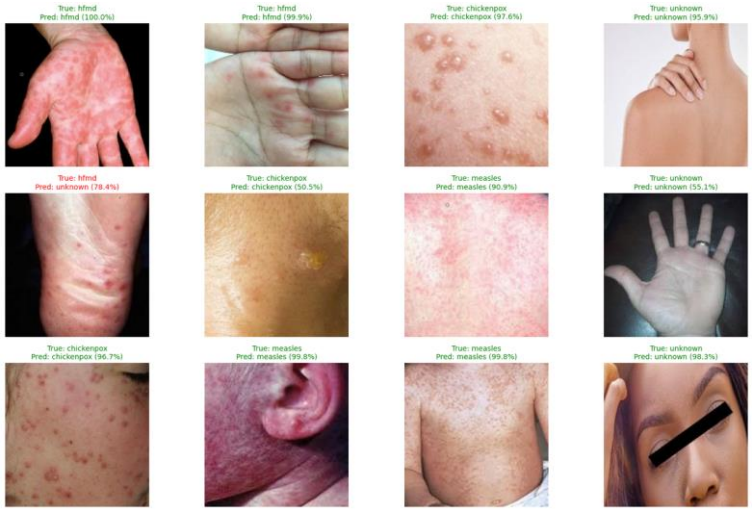


Figure 11. Sample of the test output.

Table 2. Real-World Evaluation Results.

Metric	ResNet50	VGG19	CNN
Accuracy	0.25	0.83	0.75
Precision (avg)	0.06	0.83	0.83
Recall (avg)	0.25	0.83	0.75
F1-score (avg)	0.25	0.83	0.75

4. Discussion

4.1. Optimization Impact and Model Comparison

The application of optimization strategies substantially improved the performance of the evaluated models. Initially, the ResNet50 model suffered from pronounced overfitting, evidenced by a test accuracy of 25% and validation loss nearing 10. Similarly, the Custom CNN revealed a performance gap between its training and real-world phases, suggesting limitations in model adaptability. In contrast, the VGG19 model, after architectural fine-tuning and regularization techniques like early stop-

ping and learning rate scheduling, attained an optimal balance between learning efficiency and robustness. Its final validation accuracy of 98.32%, alongside competitive real-world results, highlights its capacity to adapt effectively to clinical data. Additionally, Custom CNN preserved high precision (83%) after optimization, which suggests its strength in reducing false positives. However, its moderate recall points to missed true cases, indicating room for improvement in sensitivity. These comparative outcomes underscore the value of targeted refinement methods in mitigating overfitting and boosting generalization to unseen samples, as illustrated in Figure 12. Transfer learning models such as VGG19 clearly benefit from domain-specific adaptation, reaffirming their relevance for image-based diagnostic tasks.

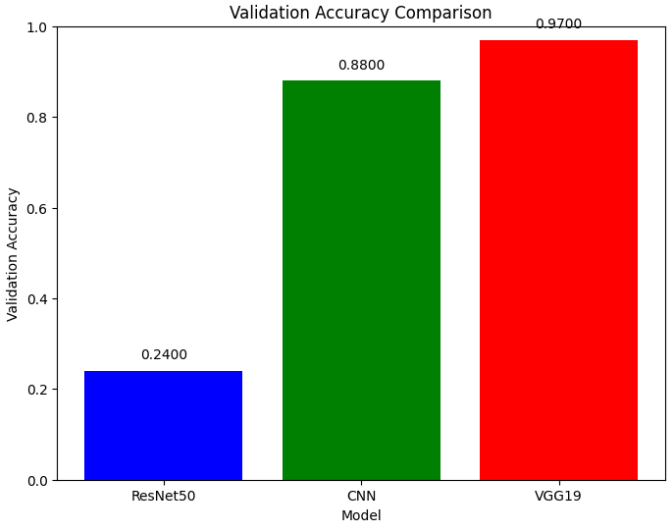


Figure 12. Comparison of models results.

4.2. Clinical Implications and Limitations

When tested under real-world conditions, model performance varied notably. VGG19 emerged as the most clinically viable candidate, achieving 83.33% accuracy with balanced precision, recall, and F1-score, each at 83%. These outcomes reinforce the model's adaptability and its potential for deployment in healthcare settings, particularly within pediatric diagnostics.

Custom CNN, despite excellent validation scores, showed a slight drop in real-world accuracy (75%). Its precision remained consistently high, indicating dependability in identifying true negatives, but its lower recall values hint at missed diagnoses. ResNet50's performance declined markedly during external testing, further confirming its overfitting tendencies and inability to generalize beyond the training dataset, as noted earlier.

Strengths of the study include:

- Integration of deep learning with clinical image analysis.
- High practical performance of VGG19, supporting its pediatric applicability.
- Consistent precision from Custom CNN, limiting false-positive rates.

Identified limitations:

- Overfitting in ResNet50 and Custom CNN, suggesting a need for more varied training data.
- Moderate recall in Custom CNN, which could impact diagnostic sensitivity.
- A limited test set (48 images), which constrains generalizability and statistical power.

Collectively, the findings underscore the promise of VGG19 for skin disease classification while emphasizing the importance of diversified datasets and refined regularization approaches to ensure model robustness across clinical environments.

4.3. Future Work

To enhance the clinical applicability of the proposed skin disease classification system, several key improvements are recommended. First, expanding the dataset to include a larger and more diverse collection of clinical images—capturing variation across age, skin tone, and geographic regions—would improve generalizability and reduce bias. Second, extending the diagnostic scope to cover additional pediatric skin conditions such as eczema, impetigo, fungal infections, and scabies would increase the system's clinical relevance. Third, integrating multimodal patient data—including symptoms, medical history, and other clinical parameters—could strengthen diagnostic accuracy beyond image-based analysis alone. These enhancements would help transition the current prototype into a robust and practical decision-support tool for deployment in pediatric and telemedicine settings.

4.4 Implications for Entrepreneurship and Innovation Theory

The integration of artificial intelligence (AI) into pediatric healthcare introduces not only a technological advancement but also a significant entrepreneurial opportunity. The results of this study align closely with established innovation and technology adoption theories, such as the Technology Acceptance Model (TAM) and the Diffusion of Innovations framework. These theories suggest that the perceived usefulness and ease of use of a new technology play essential roles in its adoption[28][29]. The high accuracy and user-friendly interface of the developed AI model demonstrate that such tools can effectively lower adoption barriers for non-specialist users, including nursery staff, pediatric nurses, and parents[30][31].

From an entrepreneurial perspective, the system represents a strong -value proposition—a cost-effective and accessible diagnostic support tool for early detection of skin diseases in children. The findings reveal a potential business model centered on cloud-based AI services (SaaS) or locally deployed solutions integrated into existing pediatric or telemedicine platforms. The path from research prototype to marketable product may progress through clinical validation, pilot testing in nurseries, and partnerships with health-tech incubators or public health authorities. Thus, this study demonstrates how domain-specific AI systems can transform academic innovation into tangible entrepreneurial opportunities that enhance healthcare outcomes.

Condensed and Focused Theoretical Framework

This research is informed by three complementary theoretical foundations: Technology Adoption, Innovation Diffusion, and Entrepreneurial Opportunity Recognition. Technology Adoption theory emphasizes the roles of perceived usefulness, ease of use, and behavioral intention in determining user engagement. Innovation Diffusion theory contributes by highlighting observable advantages and compatibility with existing practices as key factors driving the adoption of new technologies. Finally,

Entrepreneurial Opportunity Recognition theory explains how technological advancements create new markets and value chains that entrepreneurs can exploit[32][33].

Synthesizing these perspectives, the study proposes three core assumptions: (1) AI models that are transparent and clinically validated improve trust and perceived usefulness among users; (2) accessible design—through intuitive interfaces and efficient processing—enhances the likelihood of early adoption; and (3) validated real-world performance data act as a trigger for entrepreneurial ventures seeking to scale health-tech innovations. This framework provides a theoretical foundation for linking the study's empirical results to innovation management and entrepreneurship development.

4.5 Practical Implications for Entrepreneurship Education in Saudi Universities

The study's outcomes have strong implications for entrepreneurship and innovation education, particularly in Saudi universities seeking to develop the next generation of digital health entrepreneurs. Integrating the lessons from this project into academic programs can bridge the gap between classroom learning and real-world innovation[34]. The following strategies are recommended:

4.5.1. Health-Tech Venture Development Module

Introduce dedicated coursework focused on identifying healthcare challenges, designing AI-driven solutions, and navigating regulatory and ethical frameworks. Students can engage in team-based projects using real datasets, culminating in the design of a minimum viable product (MVP) ready for pilot testing.

4.5.2. Interdisciplinary Collaboration Tracks

Encourage collaboration between students of computer science, medicine, and business disciplines to co-create viable health-tech solutions. These teams can develop business models, perform stakeholder analyses, and design pilot implementation strategies.

4.5.3. Incubation and Clinical Validation Pathways

Establish partnerships between university innovation centers and local hospitals to support pilot deployment, mentorship, and ethical review processes. Providing seed funding and clinical access will enable students to validate their innovations in real-world healthcare environments.

4.5.4. Performance and Impact Evaluation

Expand assessment criteria to include not only technical accuracy but also social and commercial viability. Evaluation metrics may include user satisfaction, market readiness, and compliance with ethical and regulatory standards.

4.5.5. Policy and Ecosystem Alignment

Align educational initiatives with Saudi Vision 2030's goals for digital transformation and knowledge-based economic diversification. Embedding this alignment ensures that student projects contribute directly to national innovation priorities.

By embedding such initiatives, Saudi universities can serve as catalysts for transforming academic prototypes into commercially viable ventures, fostering a new generation of entrepreneurs equipped to advance the national health innovation ecosystem.

5. Ethical Procedures

Ethical approval and participant protection were central to this research. All image data used in this study were verified to comply with institutional ethical standards and data-use policies. For images sourced from the public Mpox Skin Lesion Dataset (MSLD v2.0), informed consent had been obtained by the original data providers. For any additional clinical validation images, the research team received Institutional Review Board (IRB) approval and documented informed consent from the legal guardians of pediatric participants.

All images were anonymized prior to analysis, and no personally identifiable information was collected or stored. Data processing was conducted using encrypted devices with restricted access. Any data sharing or secondary analysis followed strict confidentiality agreements and required prior IRB clearance. The study adhered to the principles of minimal data exposure, privacy protection, and ethical transparency throughout the research lifecycle[35].

6. Concluding Remarks and Link to Entrepreneurship

The integration of AI into pediatric healthcare presents a promising avenue for both technological advancement and entrepreneurial innovation. This research demonstrates that academic projects can evolve into practical solutions addressing critical health challenges, particularly when supported by strong institutional ecosystems. By applying an entrepreneurial lens, this study underscores how AI models, once validated, can be transformed into scalable digital ventures with measurable social and economic impact.

Embedding such research within entrepreneurship education and incubation programs in Saudi Arabia will not only enhance innovation capacity but also accelerate the translation of AI-driven prototypes into market-ready health solutions. Ultimately, the project exemplifies how the convergence of science, technology, and entrepreneurship can foster sustainable development—supporting both the health of children and the broader goals of national innovation under Saudi Vision 2030.

7. Patents

No patents have been resulting from the work reported in this manuscript.

Author Contributions: “Conceptualization, E.H.A; methodology, E.H.A and L.A.A.; software, E.H.A and L.A.A.; validation, E.H.A and L.A.A.; formal analysis, E.H.A and L.A.A. .; investigation, E.H.A and L.A.A.; resources, H.F.A.; data curation, E.H.A and L.A.A.; writing—original draft preparation, E.H.A and L.A.A.; writing—review and editing, E.H.A and L.A.A.; visualization, E.H.A and L.A.A.; supervision, S.A.; project administration, S.A.; funding acquisition, “no funding was received for this study”. All authors have read and agreed to the published version of the manuscript.”

Funding: “This research received no external funding”.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement:

The data supporting the findings of this study are publicly available in the Mpox Skin Lesion Dataset (MSLD) v2.0 on Kaggle at: https://www.kaggle.com/datasets/joydippaul/mpox-skin-lesion-dataset-version-20-msld-v20.

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Conflicts of Interest: "The authors declare no conflicts of interest".

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