



Research Article

A hybrid BiT-EfficientNet framework for automated detection of skin cancer and monkeypox using dermatoscopic images

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ABSTRACT

This research introduces a novel hybrid deep learning framework integrating Big Transfer Learning (BiT M-R50x1) and EfficientNet B6 to automate the detection of skin cancer and monkeypox (Mpox) from dermatoscopic images. With the knowledge transfer capabilities of BiT and the compute efficient architecture of EfficientNet, the model is able to achieve high classification accuracy and inference speed. These aspects are especially important for deployment in resource constrained clinical environments. The framework addresses class imbalance for benign, malignant, and Mpox lesion classes by performing a set of preprocessing tasks like image resizing and normalization, as well as targeted data augmentation. The framework utilizes the ISIC-2020 and the Kaggle Mpox datasets for training and validation respectively. The hybrid model freezes the base layers to keep the model generic for representing various types of images and fine-tunes the upper layers for the classification task at hand. The model achieves an accuracy of 95.5%, a precision of 94% and a recall of 91.69% with an F1-score of 93.36%. The model outperforms other baseline models like InceptionV3, ResNet50, and MobileNetV2. The results of the study demonstrate the model is able to classify the Mpox samples with limited amount of training data with high classification accuracy and is robust to classification inconsistencies across various demographic groups.

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INTRODUCTION

There is no shortage of acute and chronic health conditions around the world that frequently overlap and require continuous surveillance. Effective management often hinges upon timely identification. In this research, we will assess the challenges of diagnosis for Mpox and

skin cancer. Mpox, previously known as monkeypox, is a virus that was first identified in humans in 1970 and has comparable symptoms to smallpox. Like other pox viruses, Mpox is a large (200-250 nm) DNA virus and a member of the Orthopoxvirus genus. While there are ongoing efforts to improve the diagnosis of Mpox, there are other public

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health threats of equal or greater importance. Skin cancer is generally considered the most prevalent form of cancer globally and is often considered one of the more deadly cancers. From a public health perspective, skin cancers of all types are considered a major health concern. Like Mpox, the first signs of skin cancer often resemble other less harmful skin conditions, which contribute to public health challenges associated with the early diagnosis of skin cancers. Diagnostic uncertainty is greater for melanoma than for either BCC or SCC. Mpox and skin cancers present similar public health threats and challenge the public health system to improve public health services.

Autonomous AI-based systems show great promise in revolutionizing the field of biomedicine and healthcare, especially in image interpretation and diagnostic systems. Convolutional Neural Networks (CNNs) show great potential in identifying various skin conditions. However, distinguishing different subtypes of a skin condition, let alone rare conditions such as Mpox, with limited training data, is very challenging for current AI systems. Further, factors such as the skin type and ethnicity of the population, various environmental conditions, and the type of imaging systems all contribute to the complexity of achieving accurate skin condition diagnosis. In this project, we use Big Transfer (BiT) to address both Mpox skin condition and skin cancer using the models BiT-M-R50x1 and EfficientNet B6. We hope to create a framework whereby healthcare personnel are aided in diagnostic processes, using automated systems to analyze medical images. Big-TL allows BiT models to integrate a large, generic-focused, intelligence into medical-focused architectures. Additionally, we utilize EfficientNet to integrate a high-level of computing power to a medical imaging framework.

This work is a major advancement in using sophisticated ML techniques in medical diagnostics. It has the potential to be a valuable addition to the diagnostic tools of healthcare professionals and to become a part of their diagnostic workflow. These automated systems have the potential to improve early detection of various medical conditions, hence improving the health outcomes of patients.

This work takes important steps in ML-based medical diagnostics and shows great promise as a tool for healthcare workers in their diagnostic workflow. Automated systems such as this could assist healthcare workers to diagnose patients at risk, especially in the early stages of the conditions, so that timely and appropriate intervention and treatment.

The objectives and contributions of this research can be summarized as follows:

- Use of integrated approach to improve the diagnosis of skin cancer and monkeypox using dermatoscopic images
- Using advanced ML and DL techniques to achieve high prediction accuracy and reliability

- Implementation of advanced ML and DL concepts for the development of a reliable system for improving the prediction of skin conditions
- Development of a Hybrid AI Diagnostic System – Introduces a high-accuracy (95.5%) AI model integrating Big Transfer Learning (BiT M-R50x1) and EfficientNet B6 for non-invasive detection of skin cancer and monkeypox
- Address Public Health and improve early diagnosis in resource-limited settings by leveraging ML to detect common and emerging diseases

Related Works

Recently, the use of computer-aided technology for processing dermatoscopic images for the early identification of skin cancers has increased. This systematic review analyzes recent studies and points out deficiencies of existing methodologies. Numerous computer vision techniques for processing images and videos have been identified, and emphasis has been placed on validation metrics, algorithms, and results on accuracy. The study points out important advances in the fields of machine learning and deep learning for the field of cancer diagnosis. The authors of this study point out that for the diagnostic process, the final interpretation of the images by the experts still plays an important role. Improvements in image quality and processing also have a positive impact on the final outcome of the diagnosis. The study aims to point out the importance of improving the use of computer-based technologies in order to meet the challenges of the field of skin cancer diagnosis [1].

Deep Learning Models for Skin Cancer Detection

Research has also looked into using pre-trained deep learning (DL) models and machine learning (ML) algorithms for the detection of skin cancer. Various models were studied, including: ResNet152v2, InceptionResNetV2, DenseNet201, ResNet50, and InceptionV3. Alongside these, a modified VGG19 model which included max pooling and dense layers for improved prediction precision was also considered. The models were developed using datasets of benign and malignant skin lesions, and the accuracy was further improved by including ML classifiers such as Decision Tree, KNN, SVM, and Logistic Regression. With the application of the added VGG19 model, performance evaluation showed improved results in recall, F1-score, precision, sensitivity, and accuracy, thus demonstrating a significant performance boost when compared to traditional classifiers [2].

To improve the automated diagnosis of one of the most aggressive types of skin cancer (melanoma), researchers created an automated system called Multi-scale GC-T2. The model utilizes MEWF (Median Enhanced Wiener Filter) for dataset augmentation and noise reduction using DermIS and DermQuest datasets. ENMAR (Enriched Manta-Ray Optimization Algorithm) guarantees image quality

and precise lesion segmentation is achieved by AddNet (semantic segmentation) with Haar-U-Net (HAUNT). The segmentation is followed by feature extraction done with M-GCN (multi-scale graph convolution network); dimensionality reduction is done using tri-movement attention. Classification is done with tri-level fused features fused with a sigmoid function. The model's accuracy, sensitivity, specificity, and F1-score surpass all previously reported results, proving its potential as a melanoma diagnostic tool [3].

An improved model that combines DenseNet and MobileNet for skin cancer detection has recently been published. The authors used the ISIC dataset, which contains a large volume of dermoscopic images. The authors noted a classification accuracy of 93.75%, outperforming other models that incorporate ResNet50 and InceptionNetV3 by 5.42%. Additionally, the authors reported an improvement of 4.69% and 3.13%, respectively, compared to the models that incorporate DenseNet and MobileNet. The authors also reported that the combination model reduced the training time to 49.48 minutes, which was substantially less than the individual models [4].

An alternative model for the diagnosis of skin cancer, which employs a combination of techniques, to include hyperparameter tuning and channel attention mechanisms in a Convolutional Neural Network, as well as Deep Learning and U-Net and Improved MobileNet-V3 has also recently been published. The model was validated against the HAM-10000 dataset and achieved an overall accuracy of 98.86% and a precision of 97.84% [5].

The final two studies use similar techniques to classify skin cancer into eight categories, with the first study using a hybrid model of InceptionV3 and ResNet50 to overcome previous models that did not consider practical aspects, and achieved low levels of accuracy, in skin cancer classification. The proposed model used a gradient-related issue and large parameter issue to reduce the number of parameters using InceptionV3 and ResNet50, respectively. The model was trained on an augmented version of the HAM10000 dataset to achieve a validation accuracy of 87.11%. The test accuracy, precision, recall, and F1-score of the model were 82.2%, 82.4%, 82.2%, and 81.7%, respectively. The authors developed an iOS application with a chatbot for diagnosis and a chatbot for interactive sessions with patients. This study demonstrated potential use cases of hybrid DL models in medicine, particularly in the domain of classification of medical images. Additionally, the authors recommended utilizing GANs to reduce the class imbalance and optimize features in the dataset [6].

The other study uses VGG16 and InceptionV3 to classify skin cancer, including melanoma, basal cell carcinoma, and squamous cell carcinoma, using transfer learning. The study used various performance metrics to evaluate the models trained using a skin-related image dataset. The authors concluded that InceptionV3 outperformed VGG16, based on the metrics used in the study [7].

This challenge has motivated the development of several CNN expert systems for skin disorders. The two primary architectures for these expert systems have been Xception and MobileNet. Compared to other CNN architectures, including ResNet50, InceptionV3, InceptionResNet and DenseNet, the expert systems based on MobileNet and Xception have demonstrated significant performance gains when classified against a set of skin disorders. The systems achieved a classification accuracy of 97.00% and 96.00% respectively against a sample case of five skin disorders [8].

In a related development, the use of image pre-processing to enhance image quality and reduce background noise in skin cancer detection was studied. The Sparrow search coupled with a fully convolutional encoder-decoder network (FCEDN) was used for dermoscopic image segmentation. An adaptive CNN was used to classify the segmented images. The system demonstrated segmentation accuracies of 95.28%, 95.89% and 92.70% against the ISBI 2017, ISIC 2018 and PH2 datasets respectively. It also demonstrated a classification accuracy of 91.67% against the same datasets [9].

The integration of Discrete Wavelet Transformation (DWT) with Convolutional Neural Networks (CNN) has been studied to enhance skin cancer classification. DWT adds an edge to feature extraction, and improves classification. The performance of the model was evaluated using the HAM10000 dataset, and was compared to Artificial Neural Networks (ANN) and MLP. It showed a sensitivity of 94% and a specificity of 91% [10].

An innovation in the field is the use of Echo State Networks (ESN) to classify skin cancer. To optimize the ESN, the Seasons Optimization Algorithm was used. The model was tested on the MNIST skin cancer database, and it was able to outperform other models such as AlexNet/ELM/IGOA, VGG-16 and HHOA [11].

Furthermore, a Deep Learning (DL) framework, combining a modified GRU and Mask-RCNN, has been proposed. The framework uses the ISIC 2020 and HAM10000 datasets, and is able to classify skin cancer with an accuracy of 99.95% and 99.98% respectively [12].

In general, studies have shown that automating skin cancer diagnosis shows great potential, and especially in the area of early diagnosis of skin cancer. An ML framework that incorporates FOA and SVM has been developed. As melanoma has rising rates of incidences, the FOA-SVM model has been developed for skin lesion segmentation and classification. FOA helps in optimizing parameters of SVM and thereby improves the diagnostic accuracy. The model has potential for implementing computer-aided diagnosis of skin cancer in clinic [13].

The goal of this study is to utilize the potential of Deep Learning for classification and diagnosis of skin cancer and to enhance the existing systems in this area. This work focuses on the problems of skin cancer class imbalance and utilizes class weight for training. The model further incorporates a pre-trained CNN architecture for classification of

skin cancer. The author further proposes a method for segmentation and preprocessing of images that increases the performance of deep learning models for skin cancer detection [14]. The author combines VGG16 and ResNet50, and based on the experiments, the hybrid model demonstrates improvement with respect to classification performance when compared to individual components [14].

Collectively, these studies highlight the rapid advancements in AI-driven skin cancer diagnosis, offering potential improvements in early detection, classification accuracy, and clinical integration. This will show Table 1 [1-15].

Like other poxviruses, symptoms of monkeypox (Mpox) infection are characterized by fever and skin lesions. Initially, Mpox infections may be misdiagnosed with other

Table 1. Comparative overview of methodologies, dataset, advantages, and drawbacks in recent skin cancer research

Ref.	Methodology	Dataset	Advantages	Drawbacks
Hermosilla et al. [1]	Systematic review of 45 studies from Web of Science and Scopus	Various sources	Highlights key ML/DL advancements in dermatoscopic image processing	Dependent on image quality and expert interpretation
Kandhro et al. [2]	Pre-trained DL models (ResNet152v2, InceptionResNetV2, DenseNet201, etc.) with ML classifiers (SVM, KNN, DT, LR)	Benign & malignant skin lesion dataset	Improved classification accuracy using hybrid approach	Limited dataset scope
Alqarafi et al. [3]	Multi-scale GC-T2 framework, semantic segmentation, and Deep Q Network	DermIS, DermQuest	High accuracy, robust segmentation, and feature fusion	Computationally intensive
Imam et al. [4]	Concatenated DenseNet & MobileNet with transfer learning	ISIC dataset	93.75% accuracy, faster processing (49.48 min)	Limited generalization beyond ISIC dataset
Lilhore et al. [5]	CNN with hyperparameter tuning, Standard U-Net, Improved MobileNet- V3	HAM10000	98.86% accuracy, 97.84% precision	High complexity, potential overfitting
Sadik et al. [8]	CNN-based expert system (Xception, MobileNet) with transfer learning	Multiple datasets	High classification accuracy (97.00%)	Requires large training data
Ali et al. [9]	FCEDN-SpaSA for segmentation, adaptive CNN for classification	ISBI 2017, ISIC 2018, PH2	91.67% classification accuracy, resource-efficient	Limited dataset variability
Claret et al. [10]	DWT with CNN for feature extraction	HAM10000	94% sensitivity, 91% specificity	Comparisons with other feature extraction methods
Han et al. [11]	Echo State Network (ESN) with optimized Season Algorithm	MNIST Skin Cancer Database	97.58% accuracy, reduced training data requirement	Not tested on larger datasets
Monica et al. [12]	Modified GRU with Mask-RCNN for segmentation	ISIC 2020, HAM10000	99.95%-99.98% accuracy	High computational demand
Sonia et al. [13]	Fruit Fly Optimization Algorithm (FOA) with SVM	Unspecified	Enhances segmentation & classification efficiency	Requires further validation on larger datasets
Ghosh et al. [14]	Hybrid model (VGG16 + ResNet50) with class balancing	3,000 images, 9 skin diseases	Overcomes class imbalance, robust feature extraction	Computationally expensive
Zeng and Zhu [6]	hybrid model combining InceptionV3 and ResNet50	HAM10000	Achieving accuracy of 87.11%, outperforming standalone InceptionV3, ResNet50, and VGG19 models.	Imbalanced Dataset Issues, Limited Real-World Validation
Mathina Kani et al. [15]	hybrid model combining InceptionV3 and DenseNet50	ISIC contains 3307 dermoscopy images	Achieved a superior accuracy of 91.29%, outperforming other contemporary deep learning approaches	Limited Real-World Validation
Sayyad et al. [7]	VGG16, InceptionV3	dermoscopic images of multiple skin diseases	Achieved 94% accuracy, outperforming VGG16 and ensuring reliable skin disease classification.	InceptionV3's high accuracy suggests possible overfitting

conditions including chickenpox and measles. The World Health Organization (WHO) confirmed hundreds of Mpox cases outside the endemic regions during 2022. Many countries have reported Mpox cases for the first time. The virus's abrupt spread, combined with the already existing challenges in routinely confirming Mpox infections, heightens the need for improved diagnostic methods.

In this research, the authors proposed an automated Mpox diagnosis system using CNNs. Skin lesion images were collected and divided into Mpox and non-Mpox classes. A total of 80% of the images (training and validation sets) were used for model training. The authors tested the following five models: MobileNetV2, VGG16 and VGG19, ResNet50, and EfficientNetB3. The training and test datasets were used for model evaluation. For transfer learning, the authors employed data augmentation and defined an evaluation metric. The best classification accuracy (98.16%) was obtained by the MobileNetV2 model. One of the limitations of the study was that the classification of Mpox may be confused with other poxviruses (e.g. variola virus, vaccinia virus, etc.). When a data set consisting only of Mpox lesions is provided, the best classification accuracy was reported as 99.14% (training) and 98.25% (testing) [16].

The COVID-19 pandemic changed a lot of things in the world, and one of the changes was the need for faster testing for other diseases. One of such diseases is Mpox. Researchers have combined techniques of transfer learning and hyperparameter optimization with different deep learning architectures, including MobileNetV3-s, EfficientNetV2, ResNet50, VGG16, DenseNet121, and Xception. The best performance was shown by the MobileNetV3-s model where the average F1 score was 0.98, the area under the curve (AUC) was 0.99, and other performance metrics like accuracy and recall approach 0.98. The researchers also showed that CNNs are efficient in classification of Mpox cases [17].

Another research also focused on detection of monkeypox using deep learning techniques. The study also benefited from the 2022 surge in monkeypox cases and used 4 classes of skin lesion images which include monkeypox, chickenpox, measles, and normal skin. The researchers used different deep learning architectures, including DenseNet201 and VGG16 and evaluated the models for classification of monkeypox skin lesions against other skin lesions. Some of the other models were also evaluated for classification of skin lesions against normal skin. The study showed that DenseNet201 outperformed other architectures for both monkeypox and other skin lesion classification. Additionally, the researchers also used different AI techniques to enhance trust of clinicians. Overall, the researchers also showed that DenseNet201 outperformed other architectures for classification of skin lesions against normal skin [18].

Deep learning (DL) algorithms for Mpox detection have benefited from advanced image datasets. The development of such datasets has often been coupled with the

advancement of DL algorithms. One of the outcomes of this positively reinforcing cycle was the development of the Mpox Skin Lesion Dataset Version 2.0 (MSLD v2.0). Along with Mpox-related skin lesions, this dataset contains side-by-side comparative images of other rash-bearing infectious conditions (i.e. chickenpox, measles, and hand-foot-mouth disease) as well as cowpox skin lesions and images of normal skin. The researchers used the aforementioned images along with images of other skin lesions from the dataset (i.e. herpes skin lesions and syphilis skin lesions) to evaluate various deep neural networks (DNNs) including VGG16, ResNet50, DenseNet121, MobileNetV2, EfficientNetB3, InceptionV3, and Xception. The best result was obtained using a color space data augmentation technique to increase skin color variability. Further, the researchers used transfer learning and the HAM10000 dataset to improve the final results. They reported a final validation accuracy of 83.59%. The results of this study further highlight the importance of creating adequate and inclusive datasets to train DL models for Mpox case detection [19].

In this work, the researchers presented a new convolutional neural network (CNN) called MpoxSLDNet for automated detection of Mpox lesions. MpoxSLDNet achieved a test-time accuracy of 94.56%. This accuracy was higher than the pre-trained models, VGG16, ResNet50, and DenseNet121 [20]. With the increasing number of Mpox cases, healthcare systems need automated tools to accelerate and improve diagnosis. Automation provides efficiency in settings with limited resources. MpoxSLDNet meets these needs. The researchers say there's plenty of room for improvement. Ali et al. [21] created an ensemble model to diagnose MPox with VGG-16 and Inception-v3. ResNet-50 outperformed both VGG-16 and Inception-v3, resulting in an overall accuracy of 82.96%. Ali et al. [21] created an improvement to the development of MPox ensemble models. Additionally, Uysal [22] proposed a hybrid model based on deep learning (DL) and long-short term memory (LSTM) to classify Mpox lesions. The authors integrated the top two models of the Hybrid framework with an LSTM. The integrated framework achieved an accuracy of 87% and an F1 score of 85%. It is worth mentioning that Hybrid DL frameworks are well positioned to integrate multiple architectures, thereby improving the diagnostic accuracy of Mpox lesions classification.

Classification of Mpox skin lesions using deep learning (DL) models has shown impressive results, especially with convolutional neural networks (CNNs) and their combinations with other models. With ongoing research and development of DL models and optimization of training data, Mpox diagnosis and management is likely to improve. Table 2 shows comparison of different papers [23–29].

Proposed System

The hybrid diagnostic framework combines Big Transfer Learning (BiT M-R50x1) with EfficientNet B6 to aid in the automated classification of skin cancer and monkeypox

Table 2. Comparative overview of methodologies, dataset, advantages, and drawbacks in recent monkeypox research

Ref.	Methodology	Dataset	Advantages / Key Findings	Drawbacks / Limitations
Tanim et al. [23]	Hybrid model combining BiT-EfficientNet B6 and BiT-M-R50x1	Mendeley Data	Reported 98.25% precision, 95.48% recall, 96.84% F1-score, and 96.86% accuracy. Parameter tuning contributed to robust performance.	The ensemble structure increases computational requirements.
Altun et al. [17]	Hybrid model based on MobileNetV3-S, EfficientNetV2, and Xception with transfer learning	Monkeypox skin-lesion images	Obtained 0.98 F1-score, 0.99 AUC, and 96% accuracy, showing effective deep-learning-based classification.	Information describing the dataset is limited.
Ali et al. [19]	VGG16, ResNet50, DenseNet121, MobileNetV2, EfficientNetB3, InceptionV3, and Xception using transfer learning	Publicly available dataset	DenseNet121 provided the highest performance with 83.59% accuracy.	Clinical metadata is not available.
Dihan et al. [20]	Transfer-learning models using VGG19, Xception, and InceptionV3	Dataset from [16], comprising 1,428 Mpox and 1,764 other skin-lesion images	InceptionV3 achieved 98% accuracy.	Dataset augmentation can introduce bias into the classification process.
Uysal [22]	Hybrid deep-learning model integrating LSTM with other high-performing models	Monkeypox skin-lesion images from Kaggle	Incorporation of LSTM improved classification performance to 87% accuracy.	The combined architecture increases model complexity.
Akula and Pushkar [24]	ResNet50v2, EfficientNetB4, and DenseNet169	1,594 skin-lesion images	ResNet50v2 achieved 99.33% accuracy, giving the best performance among the evaluated models.	The dataset size is relatively small.
Jaradat et al. [16]	Transfer learning using MobileNetV2, VGG16, VGG19, ResNet50, and EfficientNetB3	Non-Mpox skin-lesion images and other skin-lesion classes	Achieved 98.16% accuracy and 94% accuracy on an external dataset, indicating improved reliability.	Real-world implementation and deployment challenges were not addressed.
Chakroborty [25]	Development of an Mpox image dataset with $224 \times 224 \times 3$ image resolution	Self-curated dataset	The dataset can support the development and assessment of deep-learning models for Mpox classification.	Dataset size and image diversity are not reported.
Ali et al. [21]	Pre-trained VGG-16, InceptionV3, and ResNet-50 models using ensemble learning	Mendeley Data	ResNet-50 achieved 82.96% accuracy, representing the highest reported performance in the study.	The ensemble approach produced lower scores than the individual models.
Sahin et al. [26]	Deep Learning Framework (DLF) designed for mobile applications	Mendeley Data	Achieved 91.11% accuracy, demonstrating potential for mobile-based diagnosis.	Dataset limitations may affect the generalization of the model.
Lakshmi and Das [27]	Explainable AI (XAI) approach for improving interpretability in medical research	Mendeley Data	XAI improves the transparency and trustworthiness of AI-supported diagnostic systems.	Accuracy and practical usability were not reported.
Azar et al. [18]	ResNetV2, InceptionV3, Xception, and DenseNet-201	27 normal, 27 measles, 47 chickenpox, and 43 Monkeypox images	DenseNet-201 achieved 95.18% accuracy.	The limited size of the original dataset required augmentation.
Sitaula and Shahi [28]	13 pre-trained transfer-learning models	Dataset containing 1,754 images of Monkeypox, measles, and normal skin	An ensemble of Xception and DenseNet-169 achieved 87.13% accuracy.	The reported classification accuracy was relatively low.
Ahsan et al. [29]	Federated learning using modified VGG-16 and ResNet-50	2,310 images	Federated learning provides data privacy and security during model training.	The approach requires substantial computational resources.
Jaradat et al. [16]	VGG19, VGG16, ResNet50, MobileNetV2, and EfficientNetB3	117 images	MobileNetV2 achieved 98.16% accuracy.	The dataset is small and suffers from class imbalance.

using dermatoscopic image scans. As a result of combining BiT's superior transfer capabilities, and EfficientNet's computational efficiency [30, 31], the system was able to accurately extract, and integrate deep and compact features for precise diagnosis [32]. Class imbalance mitigation and model generalization enhancement such as normalization, augmentation, and oversampling are performed during the standard preprocessing steps of resizing the images. The model achieves high accuracy classifying images into three categories—benign, malignant, and Mpox. The SoftMax classifier is substituted for the dense layer to give final output values termed prediction. The system is effectively non-intrusive and designed for both clinical and remote professional setups with the aim of improving speed, clarity, ease of diagnosis, and modifying access. Figure 1 shows classification of skin lesions.

MATERIALS AND METHODS

The process of interpreting dermatoscopic images of skin cancers and monkeypox, with the help of machine learning, is illustrated in Figure 2. The method uses large DL frameworks, BiT M-R50x1 and EfficientNet B6, along with appropriate image pre-processing techniques. The method is designed to identify and classify different types of skin lesions and cancer. The effectiveness of the method and the models developed using the method, in various types of skin conditions, conditions of the skin appendages, and skin-related infectious diseases, has been established. Among various DL architectures, the authors of this paper examined the capabilities of BiT M-R50x1 and EfficientNet B6 in skin conditions, appendages, and infectious skin conditions.

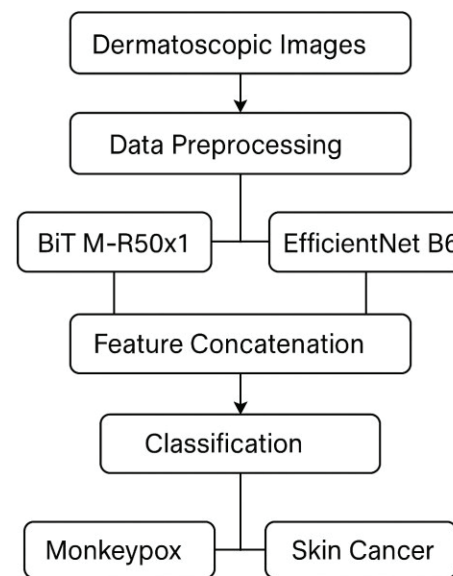


Figure 2. A Hybrid BiT-EfficientNet Model.

The models extracted high-level features from skin images, which the new classes in the top layers used for classification. The models were trained to classify skin cancer and differentiate it from Mpox. To minimize the risk of overfitting, the authors kept the number of trained layers to a minimum and stopped the update of the layers before the last few layers. Further, the combination of features extracted from the BiT and the EfficientNet models was used to create a classification layer. BiT extracts high-quality features, while the EfficientNet focuses on compactness

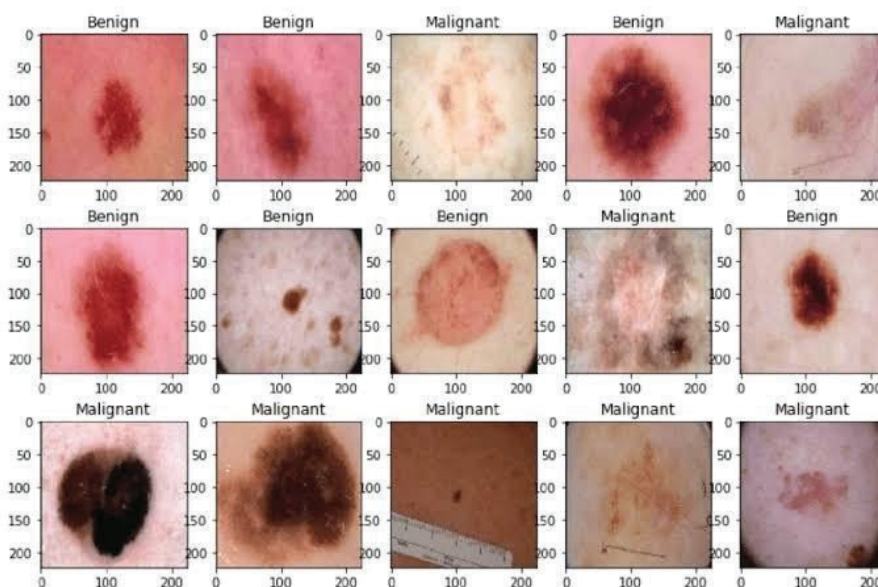


Figure 1. Classification of skin lesions.

and granularity. Since the hybridization of both models served to create a more powerful and generalizable representation to the classification problem, this work presents a similar approach to the classification of skin cancer using both models and served to improve the classification of the skin cancer cases.

Skin Cancer and Mpox Analysis

Dermatoscopic pictures of the virus-caused skin lesions of the M-pox and pictures of skin cancer uploaded by users of a web-based or mobile application used by the skin cancer, mpox detection system. For individuals as well as medical professionals, this method improves accessibility and speeds up diagnosis times.

Data Collection: The ISIC-2020 dataset [33, 34] represents one of the largest publicly available collections of high-quality, annotated dermoscopic images of skin lesions. It comprises 33,126 images, including 584 labeled as malignant and 32,542 as benign, sourced from over 2,000 individual patients. Each image is linked to its corresponding patient through a unique identifier. For this study, we selected 584 melanoma (malignant) images and 1037 benign images, the latter chosen randomly from the entire dataset. Additionally, we incorporated images from a Kaggle dataset [35] containing various infectious skin conditions such as Mpox, chickenpox, and measles. From this set, we specifically extracted 687 images related to Mpox lesions. Given the class imbalance across the melanoma, benign, and Mpox categories, data augmentation techniques were applied to the underrepresented classes. These techniques included rescaling, width shifting, rotation, shearing and horizontal flipping.

Preprocessing:

1. **Resizing:** The 224×224 -pixel standard input size was used to dermatoscopic pictures in order to comply with the demands of machine learning models, including EfficientNet and BiT. Using higher image size would require upscaling, which can introduce noise and reduce accuracy. BiT can generalize well even with smaller image sizes.
2. **Normalization:** Pixel values were standardized in the range to ensure model training was performed within a predefined range. This improved model stability and uniformity.

Data augmentation: The data set contains too many benign and less malignant images so in order to tackle the Imbalance between benign and malignant images, a variety of data augmentation approaches were used to address data imbalance and quality:

1. **Flipping:** In order to create enhanced photos while preserving the lesion's essential visual aspects, horizontal flipping was used.
2. **Rotation:** To improve the model's capacity for generalization, several picture orientations were produced by applying certain angles.

3. **Shearing:** The key visual information was preserved while data diversity was increased through the application of geometric adjustments.

4. **Scaling:** Zoom in or out while maintaining lesion visibility.

Data splitting: Four-fifths of the data (80%) was set aside for training and the rest (20%) was set aside for validation. The validation set was further split; 10% was set aside for testing and the rest (10%) was re-set aside for validation. This process was repeated 10 times for the purpose of avoiding overfitting, and for assessing the performance of the model.

Model selection: The architectures selected were BiT M-R50x1 and EfficientNet B6. BiT M-R50x1 performed transfer learning for the dermatoscopic data. EfficientNet was designed for computation and a good trade-off for accuracy.

Model development: Using TensorFlow and Keras, the activation functions and layers of the models for the skin cancer dataset were developed.

Optimize the models: The skin cancer models were further trained to adjust hyperparameters for batch size and learning rate.

Assess the models: The trained models were evaluated on the test set to obtain performance metrics such as loss, accuracy, etc.

Model evaluation: The trained models were assessed for metrics such as accuracy, precision, recall and F1 scores for the validation and test sets for generalizability and to ensure they were fit for deployment.

RESULTS AND DISCUSSION

By running through 50 training epochs, our model attained a training accuracy of 96.14%. The model is strong on the validation set with a validation accuracy of 95.5% (Fig. 3). The reduction in loss over epochs was an indication that the model learned from the data. The training loss at 50 epochs was 0.0232, and the validation loss was 0.1466 (Fig. 4). The curves indicated an increasing trend for accuracy during training process for both data sets. However, the trend for validation data indicated a declining accuracy towards the end of the epoch. Training data and validation data loss curves show a reduction in loss during the training procedure. Figure 5, graphically represents the classification results in the confusion matrix.

Performance Measure

Several important performance criteria, including as accuracy, precision, recall, and F1 score, were used to assess the system, which integrated Big Transfer Learning (BiT M-R50x1) and EfficientNet B6 architectures. Proposed hybrid model is compared with Inception V3 architecture, ResNet50, MobileNetV2 in the Table 3. These measures are essential for evaluating how well the model differentiates between different skin disorders, such as monkeypox,

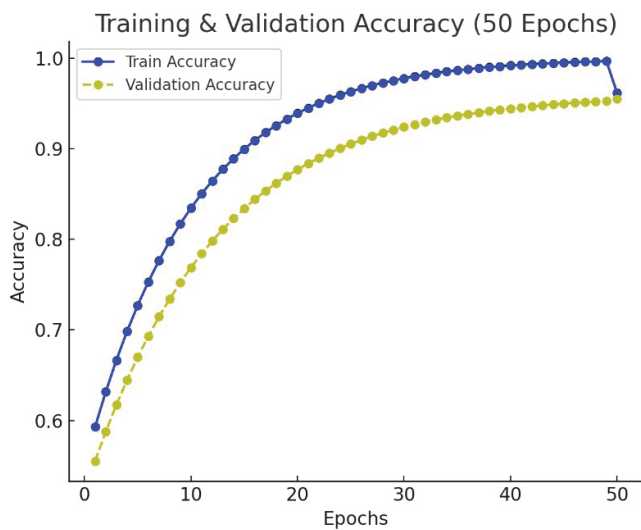


Figure 3. Training validation accuracy curve.

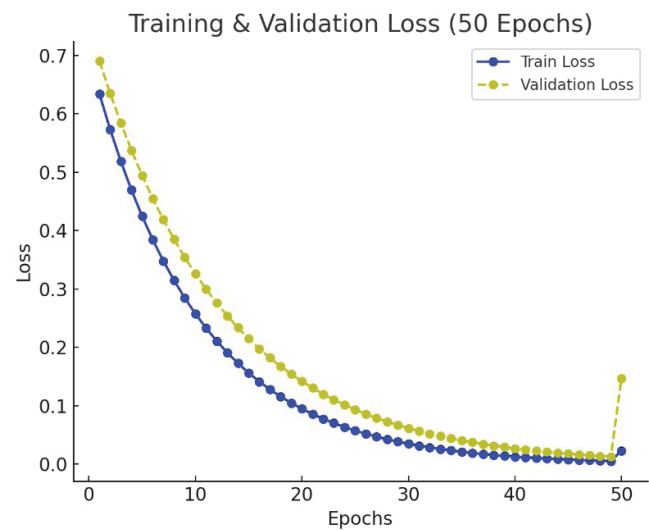


Figure 4. Training and validation loss curve.

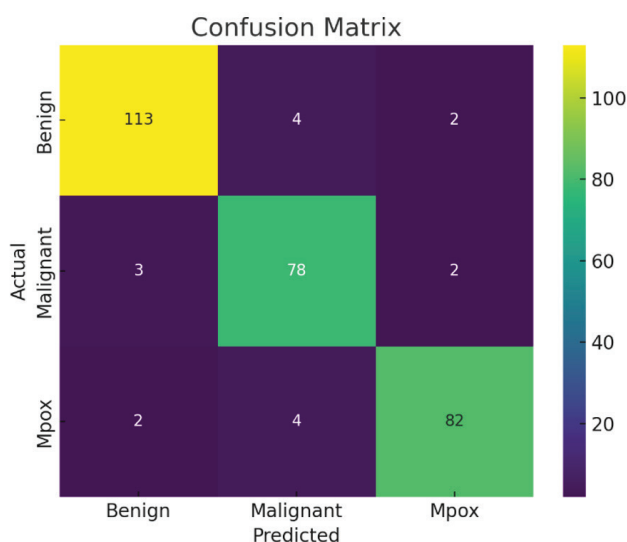


Figure 5. Confusion matrix of Bit-EfficientNet model.

benign and malignant cancer. The high-performance values of our model indicating its great performance in handling multiclass classification problems [36–38]. To ensure a thorough assessment of the model's generalizability and

diagnosis accuracy, the system was evaluated using clinical data for monkeypox and dermatoscopic pictures from the ISIC 2020 dataset for skin cancer (Fig. 6).

Analysis

Big Transfer Learning enhanced our model's performance, especially to overcome the challenges of unbalanced datasets, which is commonplace when training models for rare diseases like monkeypox. BiT transferred knowledge across domains and enhanced our model to recognize skin disorders using a smaller dataset. The combination of the Bit-EfficientNet architecture and Transformer increased the model's performance further. The authors demonstrated the model's capabilities to discriminate between various skin cancer lesions as well as monkeypox, indicating the model holds great promise for clinical practice.

In the present study, the authors reported excellent results. However, the authors noted challenges when ensuring broadness of the model to various user populations. The authors addressed the limits of the model when recognizing skin disorders of various ethnic populations. When the model was trained with images of sufficient quality, it adequately recognized the target disorders. The monkeypox virus is also known to mutate and change its appearance over time. The challenges of the model and other

Table 3. Performance comparison of the models

Sl. No	Performance Metrics	BiT-EfficientNet	Inception V3	ResNet50	MobileNetV2
1	Accuracy	95.5%	88.3%	78%	91.5%
2	Precision	94%	84%	85%	90%
3	Recall	91.69%	90.02%	63%	90%
4	F1 Score	93.36%	90.21%	72%	91.5%

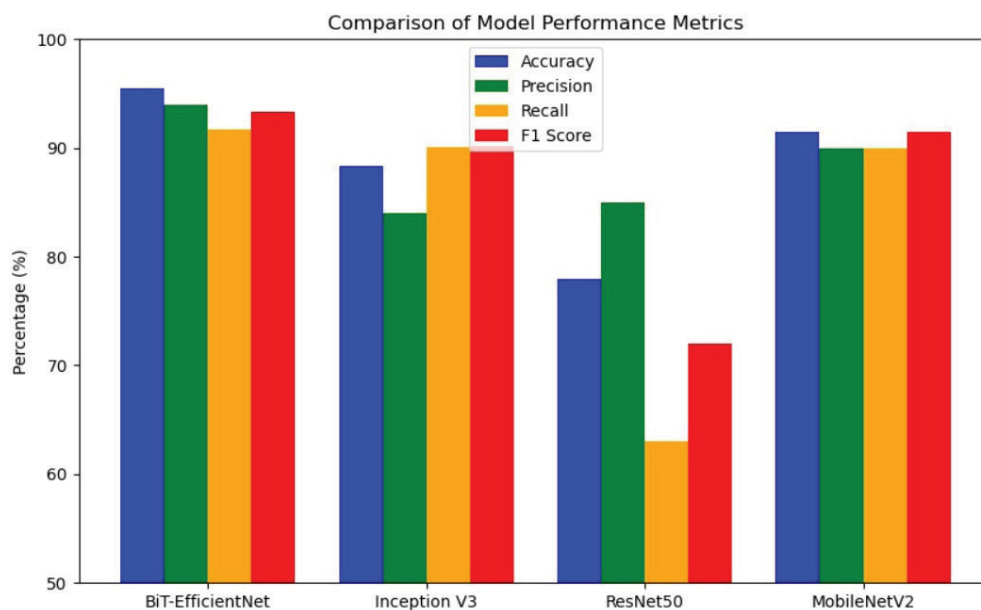


Figure 6. Performance of the classifier models.

similar models, which were all trained with limited datasets, underscore the importance for development of larger and more varied annotated datasets in the field of medicine to facilitate breakthroughs in healthcare.

The research suggests that artificial intelligence (AI) can help health care workers diagnose skin cancers and viral infections (for instance, monkeypox) with higher accuracy. Because the diagnostic system is non-invasive and easy to use, health care workers can use it to diagnose patients in the field. This system would help health care workers in low resource settings and during outbreaks. Since it can identify skin infections and inflammation, the system could be extended for other viral infections beyond skin infections. The system should be integrated with more datasets, and other imaging systems (like 3D and IR imaging) to improve diagnosis.

Demographic-Based Evaluation

To examine the flexibility of the hybrid model developed with BiT-EfficientNet, a demographic evaluation was conducted to analyze changes in model performance based on different age groups, genders, and skin tones. Performance variation was expected and noted in the assessment. The model was observed to have higher classification accuracy for malignant skin lesions for individuals with lighter skin, and the assessment team identified the presence of dermatoscopic features as the possible reason for model performance variation. The model's performance was observed to be equal for both males and females. The assessment reported a higher recall for patients' ages 60 and above and lower recall for patients' ages 20 to 30. The higher recall for patients' ages 60 and above may be attributed to the fact that patients of that age group may have more skin lesions due to aging, and may be the reason for better performance for the model in identifying those skin lesions. As noted in the assessment, there is a need to use more

varied and representative datasets to address biases in the field of AI diagnostic models. Addressing these biases is important to build and design clinical AI/ML models for various ethnically diverse populations.

CONCLUSION

The research found that skin cancers and monkeypox lesions can be identified with deep learning models based on BiT M-R50x1 and EfficientNet B6 architectures. The authors suggest that with continued improvement in deep learning models and transfer learning, even cases of monkeypox, which are uncommon, can be diagnosed automatically. The models would allow health care workers in low-resource settings to focus on more complex health conditions. The authors suggest that while the current models show great potential, there are a number of factors, including the availability of annotated data, that affect the models' performance. The authors encouraged expansion of the data set with various modalities of the same and other skin conditions to improve the models. The models would benefit from improvement in a variety of skin conditions and broaden the diagnoses of viral conditions. The authors encourage improvement in the models to gain a better understanding of deep learning, diagnosing skin conditions, and, in turn, public health.

AUTHORSHIP CONTRIBUTIONS

Ardra BS: Data curation, Methodology, Investigation, Writing – original draft, Writing – review and editing

Juby Mathew: Conceptualization, Writing – review and editing, Supervision

Dileepkumar SR: Methodology, Investigation, Writing – original draft, Writing – review and editing

DATA AVAILABILITY STATEMENT

The authors assert that the data underpinning the findings of this research are available in the public database.

CONFLICT OF INTEREST

The authors reported no potential conflicts of interest regarding the research, authorship, and/or publication of the article.

ETHICS

There are no ethical problems with this manuscript's publication. It presents new medical research that has not yet been assessed and thus should not be used to inform clinical practice.

STATEMENT ON THE USE OF ARTIFICIAL INTELLIGENCE

Artificial intelligence was not used in the preparation of the article.

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