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Machine Learning Approaches for Predicting Monkeypox Disease

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***Abstract* - The spread of monkeypox virus around the world to more than 40 countries outside Africa has developed into a critical public health issue. Early detection of monkeypox becomes challenging since doctors must rule out chickenpox and measles symptoms. The detection of monkeypox lesions through computers functions as an essential monitoring instrument for identifying possible infection cases when PCR testing is challenging to access. A combination of machine learning algorithms could perform automatic lesion identification although this approach requires enough available training data. A standard data collection for monkeypox lesion images does not exist at present. The research work delivers Monkeypox Skin Lesion Dataset (MSLD) that combines photos of monkeypox lesions alongside pictures of chickenpox and measles skin injuries. These images derive from news platforms in addition to blogs and case reports that people can access through the public domain. The data augmentation process occurs during the execution of a three-fold validation experiment. Support Vector Machines (SVM) serve as part of various pre-trained machine learning models during disease classification at the subsequent stage. The system operationalizes three separate models as an ensemble modeling approach. Staff members construct a web-based application that permits remote screening assessments for monkeypox disease through the internet interface. The good results from our initial dataset require careful consideration because expanded observational research on larger datasets will improve prediction accuracy.**

Keywords: Monkeypox, SVM, Disease classification, Ensemble model, Generalizability, Accuracy, Case reports, Data augmentation, raining data and Monkeypox Skin Lesion Dataset.

I. INTRODUCTION

The rapid worldwide transmission of monkeypox brings essential public wellness attention because the disease spreads outside its historical African areas. The early diagnosis of monkeypox remains challenging since its symptoms resemble those of both chickenpox and measles which make these skin conditions indistinguishable for patients. PCR tests are scarce across various regions worldwide especially those with constrained resources. There is an immediate need for alternative detection systems that need to be accessible and also fast and reliable.[1] A system using machine learning technology analyzes monkeypox lesion pictures to quickly identify and classify them so healthcare workers can perform effective disease detection at various facility testing locations. The new dataset production from this research enhances detection methods for both monkeypox and associated skin illnesses by developing deep learning algorithms.

A. Objective of the study

The essential purpose of this study focuses on creating an automatic machine learning system capable of detecting and categorizing monkeypox lesions. The research relies on the newly established Monkeypox Skin Lesion Dataset (MSLD) to detect monkeypox lesions among patient conditions consisting of chickenpox and measles. [2] The research applies Support Vector Machines (SVM) deep learning algorithms for quicker monkeypox detection and speed up appropriate medical treatment. The research creates an internet-based platform to enable doctors to diagnose monkeypox through a web-prototype while raising diagnostic capabilities in places without conventional testing systems.

B. Problem Statement

The worldwide migration of monkeypox causes extensive public health administration problems by requiring health care professionals to distinguish between monkeypox signs and those of chickenpox and measles. The inability to detect monkeypox early becomes more difficult because areas lack diagnostic tools such as PCR tests. Public health needs an urgent development of computerized software which detects monkeypox lesions apart from other skin issues without delay.[3] Research-based solutions enable healthcare providers to develop early monkeypox detection capabilities

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through classification assistance systems in areas lacking laboratory facilities.

C. Scope of the Study

The research develops the Monkeypox Skin Lesion Dataset (MSLD) that combines pictures of monkeypox lesions with dermatological images of chickenpox and measles. The research examines if Support Vector Machine with ensemble techniques leads to the best outcomes in lesion classification analysis. The web application development process emphasizes building an online platform to screen for monkeypox which will improve the detection of initial disease manifestations. The study establishes a dataset for disease detection which trains models by conducting evaluations before presenting a usable application to increase disease recognition capabilities. [4]

II. RELATED WORK

The study presents a new deep learning methodology which makes predictions about human monkeypox disease through image-processing methodology. The authors constructed a deep learning model to search and categorize monkeypox manifestations from medical images with the goal to enhance medical diagnosis and early identification.[5]

Deep learning systems function as an automatic system to detect skin lesions connected to monkeypox within this research. The authors gathered a substantial collection of web scraped images featuring healthy and unhealthy skin for handling training data limitations. The image classification from these pre trained models employed VGG-16, ResNet50 and InceptionV3 that operated on a range of categories between monkeypox, measles, chickenpox and healthy skin. Visual modeling techniques demonstrated effective operation when diagnosing monkeypox lesions with minimal image sources.[6]

Seven specific deep learning models were developed in this study for monkeypox disease diagnosis purposes. The data included medical images from different sources that required training for models to achieve gradual identification and classification of monkeypox lesions. The research aimed to enhance diagnostic precision while developing a dependable evaluation method for healthcare workers to diagnose monkeypox.[7]

This paper reviews systematic research involving artificial intelligence (AI) applications for monkeypox topics. Research within this study group itself into four main fields including diagnostic testing along with epidemiological modeling together with drug and vaccine discovery as well as media risk management. Multiple machine learning and deep learning algorithms received performance evaluation as part of studying whole AI applications for monkeypox combat.[8] A diagnostic model uses artificial intelligence methods to detect monkeypox infections according to this proposition. The model's purpose was to detect monkeypox through analyzing clinical symptoms together with medical data to determine infection probabilities.

This research implements Decision Tree (DT), Logistic Regression (LR), Naive Bayes (NB), Support Vector Machine (SVM), Random Forest (RF) and K-Nearest Neighbors (KNN) among six machine learning models for predicting monkeypox disease. A set of different monkeypox-related features exists within the dataset while the authors used accuracy and precision and recall and F1 score to evaluate model performance. Research aims to determine the machine learning algorithm which provides optimal early detection of monkeypox to improve public health reaction. [9]

The combination of research work achieves machine learning advancement in public health responses to emerging infectious diseases by integrating machine learning diagnostics for early monkeypox detection and diagnosis.

III. PROPOSED SYSTEM

The research develops combination models from SVM supervised learning algorithm together with MobileNet lightweight seamless convolutional neural network (CNN) for image classification between chickenpox and measles and healthy and monkeypox. The combination between MobileNet and SVM enables efficient MobileNet images extraction and optimal decision boundary generation from SVM for specific classification tasks. The initial step of the MobileNet extracts features from input images before SVM uses those features for modeling and classification. The joint system achieves peak efficiency and boosts the model's generalization ability to deliver better class discrimination outputs. [10] The model evaluation process consists of accuracy metrics for overall prediction correctness and confusion matrix analytics for counting true and false predictions of positive and negative cases. The evaluation technique helps understand how well the model categorizes information by class while finding potential wrong allocations to improve accuracy. The obtained metrics help us determine our hybrid model's ability to diagnose illness from images by providing assurance about its accurate and dependable operation.

A. Data Collection

The data collection module functions by gathering images that will be used for both model testing and training processes. A total of four image groups have been gathered

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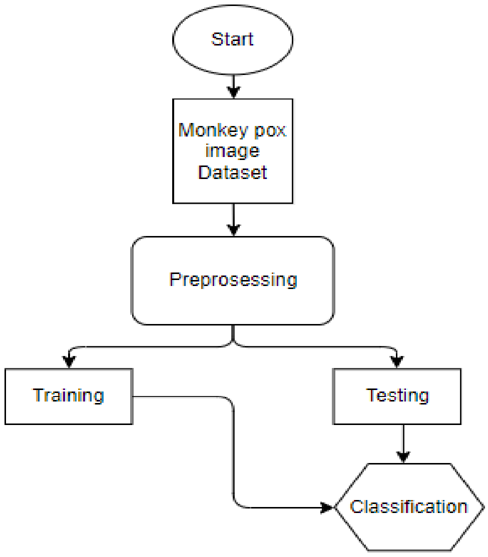
comprising chickenpox and healthy images alongside monkeypox and measles. The images for these four classes were gathered from the Kaggle platform at a total of around 800 specimens. Each picture category presents numerous examples to help the model develop generalization abilities for disease identification through visual learning patterns. The applied dataset serves as a fundamental component for building an effective classification model because real-life examples enable the model to learn and because different image patterns make the model perform better at recognizing various conditions without specializing to a single pattern so it demonstrates strong generalization capabilities on new data.

B. Preprocessing Step

Raw image data must undergo preprocessing to make them suitable for model processing. A standard size of 150-by-150 pixels needs to be implemented because it balances computational resources with data consistency. Prior to performing these operations they must first process each image before uniformly resizing all 150 by 150 pixels images. A neural network requires normalized pixel arrays for input so the initial images are modified into array formats through normalization. [11] The image dimensionality is enlarged as part of preprocessing in order to support single batch processing while preprocessing functions modify images before MobileNetV2 accepts them. The image adjustment for the model becomes possible through this vital process which enables a universal design method for effective training.

C. Model Building

This module incorporates MobileNetV2 with SVM for developing an image classification structure. MobileNetV2 serves as a compact convolutional neural network system which functions mainly for extracting features from input data. This network design focuses on efficient performance for mobile and resource-constraint devices therefore it becomes a preferred selection for real time inference applications. [12] The depth separable convolutions implementation makes the model extremely efficient since it decreases parameter count while maintaining accurate performance. The SVM classifier receives image features extracted by MobileNetV2 before executing the task of determining final classifications. Through the maximum margin approach SVM locates its optimal separating hyperplane to achieve the best classification boundaries. Through the implementation of SVM in this model it becomes possible to achieve precise differentiation between four classes including chickenpox, measles, healthy and monkeypox using MobileNetV2 feature inputs.[13] The integration of MobileNetV2 with SVM achieves optimal efficiency because the framework enables rapid performance of feature extraction while simultaneously accelerating the classification operation with SVM. Image separation through the process creates training and testing domains while pictures from training serve model development needs. MobileNetV2 operates on train images which produce meaningful features for extraction from each element. SVM performs classification using properties obtained from the trained basis. During training the model demonstrated the ability to understand distinct characteristics within the disease classes (measles, chickenpox, healthy, monkeypox). Given MobileNetV2 features the SVM finds the maximum separating hyperplane that divides input data classes. The model trains SVM parameters through incremental error minimization throughout the training process. The model development process includes an automatic verification of absolute accuracy and generalization capabilities for the resulting model. [14] The backpropagation optimization with gradient descent enables the training process which makes the model ready for test data evaluation. The model requires the ability to correctly classify fresh images among the four categories to satisfy application requirements in operational environments.



D. Model Evolution

The evaluation requires two key metrics which include accuracy and confusion matrix after the model completion. The accuracy provides a basic evaluation method that measures correct output frequency relative to model prediction counts. The metric communicates about the overall capability of the model to produce accurate results across all categories. A confusion matrix helps researchers gain an in-depth understanding of model performance evaluation. The predictions are split into four categories according to the true/false values and positive/negative attributes in each class within the confusion matrix. The confusion matrix

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demonstrates both the misclassified classes along with their degree of inaccuracy.[15] Together these metrics let the model performance evaluate while showing which adjustments are required for better model outcomes.

IV. RESULTS AND DISCUSSION

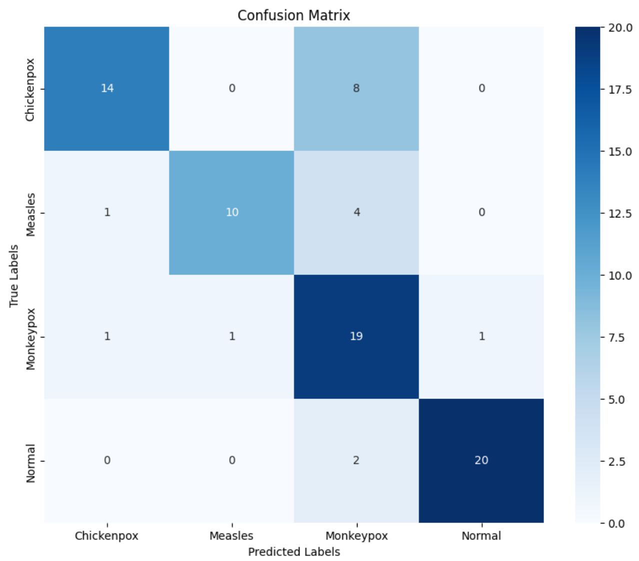

Figure 1 Confusion Matrix of hybrid Model

The model achieves remarkable success in detecting normal images and misses only two observations. Two pictures identified by the model as "Measles" belong actually to "Monkeypox" class and an additional picture incorrectly matched to "Normal." Eight images from the "Chickenpox" category appeared to the model as "Monkeypox" while "Measles" class showed with 8 misclassified examples as "Monkeypox."

V. CONCLUSION

The system determined by machine learning allows for earliest possible detection and classification of monkeypox disease through multiple research-based components. The combination of MobileNetV2 with SVM creates an efficient method to classify monkeypox against chickenpox and measles through Monkeypox Skin Lesion Dataset (MSLD). The classification results demonstrate positive findings where "Normal" category achieved high accuracy yet there were some instances of incorrect classifications that mostly misidentified chickenpox lesions. The web-based screening option created as a web prototype improves system applicability by offering speedily available diagnostics that work well in resource-constrained environments. The findings are based on limited data despite requiring additional widespread and diverse data testing for establishing wider model applicability.

VI. FUTURE ENHANCMENT

In order to further enhance the potential reliability and accuracy of the system, the following future improvements are proposed:

1. The current dataset is limited both, in size and diversity. Increasing the number of images across all classes and incorporating more diverse sources can help the model generalize better to new data, improving robustness in real-world applications.
2. The inclusion of additional diagnostic features such as demographic information, clinical history, or genomic data could help to distinguish between diseases with similar symptoms in future studies.
3. Exploiting other state-of-the-art deep learning architectures such as ResNet or EfficientNet, or perhaps combining this with ensemble learning techniques, could pave the way for improving the overall performance in classification, thus diminishing the misclassifications that occur mostly in cases that are difficult such as chickenpox. [16]
4. Developing a real-time detection system based on mobile allows healthcare providers working in remote conditions to readily utilize the diagnostic system while on the move a stride toward wider outreach and improved accessibility. If the system were to be extended with various dermatological diseases sharing a group of symptoms, it could make the model a more expansive tool for skin disease diagnosis and differentiation, thereby serving a greater variety of medical diagnoses.

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