An efficientnet to classify monkeypox-comparable skin lesions using transfer learning

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ABSTRACT

Monkeypox is an infectious illness caused by the DNA-based monkeypox virus, which has raised public health concerns due to its rapid transmission to over 50 countries. Direct physical interaction with infected humans or infected animals is the main reason behind the spread of this virus. The appearance of skin problems such as smallpox and rashes are the most frequently reported symptoms of this virus. Since cases of monkeypox are increasing rapidly around the world, stopping the spread of this zoonosis by providing early diagnosis and treatment is crucial before the emergence of a pandemic similar to COVID-19. In this study, we aim to propose a transfer learning-based approach using the EfficientNet-B0 architecture to identify monkeypox subjects by using skin lesion image samples. However, distinguishing monkeypox from other comparable infectious skin illnesses like chickenpox and measles is challenging. Therefore, additionally, this study identifies other diseases that also cause blisters and rashes on the skin, like chickenpox, and measles. During the data distribution phase, 5-fold cross-validation is used to validate the work's reliability by assuring that every sample is utilized for training and validation. For the evaluation of the model's classification performance, accuracy and loss are recorded for each training epoch. Moreover, precision, recall, F1-score, and confusion matrix are generated upon completion of the model training. This proposed approach is experimented on a public dataset and has shown remarkable performance by providing an overall 96.53% classification accuracy, 96.57% precision, 96.53% recall, and 96.52% F1-score.

KEYWORDS

Deep learning; EfficientNet; Monkeypox; Skin lesions; Transfer learning

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