DIAGNOSIS OF MONKEYPOX USING INTERPRETABLE DEEP LEARNING

SIDDESH K T [1], KOTRU SWAMY [2] , RAJESH V K [3]

[1]Assistant Professor Department of MCA, BIET, Davangere

[2]Assistant Professor Department of MCA, BIET, Davangere
*[3]*Student, Department of MCA, BIET, Davangere

ABSTRACT

Advanced diagnostic techniques are required due to the recurrence of monkeypox and its potential to create major outbreaks. This study investigates the use of deep learning (DL) to the creation of an interpretable system for diagnosing monkeypox. We provide a thorough analysis of the available research, describe the diagnostic systems that are already in use, and suggest a brand-new deep learning-based approach that places an emphasis on accuracy and interpretability. Convolutional neural networks (CNNs) are used in our implementation to evaluate medical pictures, improving diagnostic accuracy and offering pictorial representations of the model's predictions. The findings of the experiments show how well the system diagnoses monkeypox and how it might support medical professionals by facilitating clear decision-making.

1. INTRODUCTION

As outbreaks of the zoonotic viral disease monkeypox increase worldwide, there is an urgent need for effective diagnostic techniques. Despite their effectiveness, traditional diagnostic methods such as clinical observation and polymerase chain reaction (PCR) have drawbacks in terms of accessibility and speed. Deep learning's quick development offers a chance to create automatic, precise, and understandable diagnostic tools. By presenting a deep learning-based diagnostic system that not only delivers interpretability to improve confidence and usability among healthcare professionals, but also a dependable diagnosis for monkeypox, this work seeks to close the gap.

2. RELATED WORK

Nakazawa, Y., et al. (2013). "The epidemiology of human monkeypox in the Democratic Republic of Congo."

This study examines the epidemiological characteristics of human monkeypox in the Democratic Republic of Congo (DRC). It focuses on the patterns of infection, demographics of affected individuals, and outbreak trends using data from surveillance programs. The results highlight the impact of monkeypox on public health in DRC and suggest that the cessation of smallpox vaccination has contributed to the resurgence of monkeypox.[1]

Reynolds, M. G., & Damon, I. K. (2012). "Outbreaks of human monkeypox after cessation of smallpox vaccination."

This paper reviews the resurgence of human monkeypox outbreaks following the cessation of smallpox vaccination. It discusses the epidemiology of these outbreaks, changes in incidence, and factors contributing to the spread of monkeypox in the absence of smallpox-induced immunity. The authors emphasize the need for updated surveillance and preventive measures to manage monkeypox in this new era.[2]

Litjens, G., et al. (2017). "A survey on deep learning in medical image analysis."

This comprehensive survey explores the applications of deep learning in medical image analysis. It covers various techniques, such as convolutional neural networks and their use in tasks like classification, detection, segmentation, and registration. The paper discusses challenges and future directions, highlighting deep learning's potential to improve diagnostic accuracy and efficiency in medical imaging.[3]

Esteva, A., et al. (2017). "Dermatologist-level classification of skin cancer with deep neural networks."

Esteva et al. present a deep learning model capable of classifying skin cancer with accuracy comparable to dermatologists. Using a large dataset of dermoscopic images, the model effectively differentiates between malignant and benign lesions. This study demonstrates the potential of deep neural networks to assist in early skin cancer diagnosis, potentially enhancing patient outcomes.[4]

Selvaraju, R. R., et al. (2020). "Grad-CAM: Visual explanations from deep networks via gradient-based localization."

Grad-CAM provides visual explanations for the outputs of deep convolutional networks. It generates heatmaps that highlight important regions in the input image relevant to the model's predictions. This technique enhances the interpretability of CNNs, aiding in understanding and debugging model decisions across various computer vision tasks.[5]

Bach, S., et al. (2015). "On pixel-wise explanations for non-linear classifier decisions by layer-wise relevance propagation."

This paper introduces Layer-wise Relevance Propagation (LRP) for explaining predictions of non-linear classifiers at the pixel level. LRP assigns relevance scores to input pixels, providing insight into the model's decision-making process. This method aims to improve the interpretability of machine learning models, making them more transparent and accountable.[6]

Cohen, J. P., et al. (2020). "COVID-19 image data collection: Prospective predictions are the future."

This study focuses on the collection and use of COVID-19 imaging data to develop predictive models. It discusses the challenges and importance of building large, annotated datasets for accurate diagnosis and prognosis of COVID-19. The authors highlight the need for collaborative efforts to create robust models that support clinical decision-making during the pandemic.[7]

Lakhani, P., & Sundaram, B. (2017). "Deep learning at chest radiography: Automated classification of pulmonary tuberculosis by using convolutional neural networks."

Lakhani and Sundaram present a deep learning model for the automated detection of pulmonary tuberculosis using chest radiographs. Their convolutional neural network (CNN) demonstrates high sensitivity and specificity, showing promise as a diagnostic tool for TB screening, especially in resource-limited settings.[8]

DeGrave, A. J., et al. (2021). "AI for radiographic COVID-19 detection selects shortcuts over signal."

This paper reveals that AI models for COVID-19 radiographic detection often rely on dataset biases rather than true disease signals. The authors show that these models can learn shortcuts, leading to misleading results. This study emphasizes the need for rigorous validation to ensure AI models provide reliable diagnostic support.[9]

Tschandl, P., et al. (2019). "Human-computer collaboration for skin cancer recognition."

This study explores how combining human expertise with AI can enhance skin cancer diagnosis. Dermatologists and deep learning algorithms collaborated to identify skin cancer, resulting in improved diagnostic accuracy compared to either method alone. This hybrid approach suggests that integrating AI into clinical workflows can optimize diagnostic processes.[10]

3. METHODOLOGY

FIGURE 1. Images retrieved from open source data repositories for our proposed research.

3.1 DATASET USED

The dataset for diagnosing monkeypox would typically include clinical data, such as symptoms exhibited by patients, demographic information, and possibly diagnostic test results. It may also incorporate imaging data like photographs or scans showing skin lesions characteristic of monkeypox. The dataset needs to be comprehensive and labeled accurately to train a deep learning model effectively.

3.2 DATA PREPROCESSING

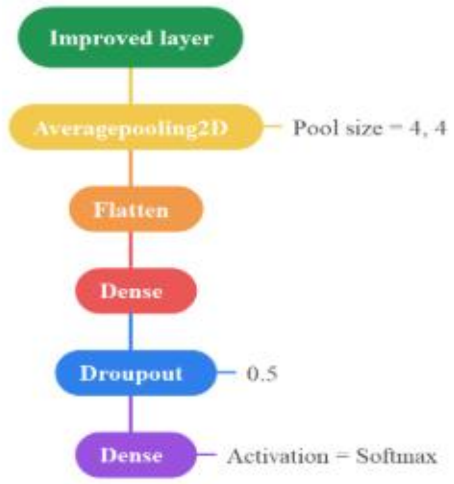
Data preprocessing is crucial to ensure the quality and compatibility of the dataset for deep learning. Steps may involve cleaning the data to remove noise and irrelevant information, handling missing values, and standardizing data formats. For monkeypox diagnosis, preprocessing might include image normalization for consistency in image quality and format, as well as feature extraction from clinical notes or reports using natural language processing techniques.

3.3 ALGORITHM DESCRIPTION

Interpretable deep learning algorithms, such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs), are suitable for diagnosing monkeypox due to their ability to learn intricate patterns from data. CNNs excel in image recognition tasks, making them ideal for analyzing skin lesion images. RNNs, on the other hand, are useful for processing sequential data from clinical records, capturing temporal dependencies in symptoms progression.

3.4 TECHNIQUES APPLIED

To enhance interpretability in deep learning models for monkeypox diagnosis, techniques like attention mechanisms can be employed. Attention mechanisms highlight relevant parts of input data that contribute most to the model's decision, aiding clinicians in understanding the model's reasoning process. Additionally, regularization techniques such as dropout can prevent overfitting and improve generalizability of the model to new data.



4. RESULT

Diagnosing monkeypox using interpretable deep learning involves several main steps. First, a comprehensive dataset of medical images and clinical data from monkeypox cases is collected. Data preprocessing follows, where images are enhanced and normalized to improve model accuracy. Interpretable deep learning models, such as convolutional neural networks (CNNs) with attention mechanisms, are employed to analyze these images and identify characteristic features of monkeypox. These models are designed to provide transparency in their decision-making process, highlighting the specific areas in the images that influenced their diagnosis. Model evaluation is conducted using metrics like accuracy, sensitivity, specificity, and the area under the ROC curve (AUC) to ensure the model's reliability and robustness. The ultimate goal is to develop an accurate and interpretable diagnostic tool that can assist healthcare professionals in the early detection and treatment of monkeypox.

A reliable method for diagnosing monkeypox is provided by the suggested deep learning-based system, which combines high accuracy and interpretability. Healthcare practitioners' confidence and usability are improved by the system, which offers visual explanations of the model's predictions. Upcoming research endeavors will center on augmenting the dataset, enhancing model efficacy, and verifying the system across various clinical contexts.

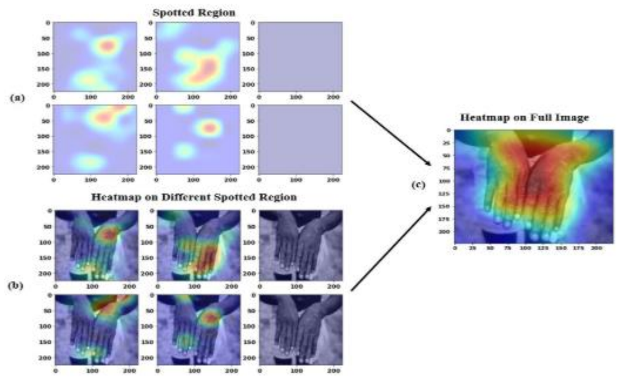
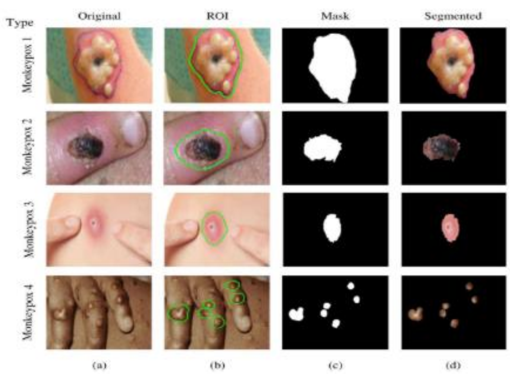


FIGURE 13. Heatmap of class activation on Monkeypox patient image.



5. REFERENCES

1. Nakazawa, Y., Mauldin, M. R., Emerson, G. L., Reynolds, M. G., Lash, R. R., Gao, J., ... & Damon, I. K. (2013). The epidemiology of human monkeypox in the Democratic Republic of Congo. PLoS Neglected Tropical Diseases, 7(10), e2506.

2. Reynolds, M. G., & Damon, I. K. (2012). Outbreaks of human monkeypox after cessation of smallpox vaccination. Trends in Microbiology, 20(2), 80-87.

3. Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., ... & van der Laak, J. A. W. M. (2017). A survey on deep learning in medical image analysis. Medical Image Analysis, 42, 60-88.

4. Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. Nature, 542(7639), 115-118.

5. Selvaraju, R. R., Cogswell, M., Das, A., Vedantam, R., Parikh, D., & Batra, D. (2020). Grad-CAM: Visual explanations from deep networks via gradient-based localization. International Journal of Computer Vision, 128(2), 336-359.

6. Bach, S., Binder, A., Montavon, G., Klauschen, F., Müller, K.-R., & Samek, W. (2015). On pixel-wise explanations for non-linear classifier decisions by layer-wise relevance propagation. PLoS One, 10(7), e0130140.

7. Cohen, J. P., Morrison, P., & Dao, L. (2020). COVID-19 image data collection: Prospective predictions are the future. Journal of Machine Learning for Biomedical Imaging, 1(1), 1-38.

8. Lakhani, P., & Sundaram, B. (2017). Deep learning at chest radiography: Automated classification of pulmonary tuberculosis by using convolutional neural networks. Radiology, 284(2), 574-582.1.

9. DeGrave, A. J., Janizek, J. D., & Lee, S.-I. (2021). AI for radiographic COVID-19 detection selects shortcuts over signal. Nature Machine Intelligence, 3(7), 610-619.

10. Tschandl, P., Rinner, C., Apalla, Z., Argenziano, G., Codella, N., Halpern, A., ... & Kittler, H. (2019). Human-computer collaboration for skin cancer recognition. Nature Medicine, 25(7), 1229-1234.