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Monkeypox Classification

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***Abstract*- The rapid spread of monkeypox (mpox) across several nations has made the current outbreak a serious public health concern. Effective management and treatment of mpox depend on early diagnosis and detection. In light of this, the goal of this study was to identify and evaluate the top-performing model for mpox detection utilizing classification models and deep learning techniques. In order to accomplish this, we analysed the accuracy levels of five popular pretrained deep learning models (VGG19, VGG16, ResNet50, MobileNetV2) and assessed how well they performed in mpox detection. The models accuracy, recall, precision, and F1-score were among the criteria used to evaluate their performance. The MobileNetV2 model performed the best in classification, according to our trial data, with an accuracy level of 98.16%, recall of 0.96, precision of 0.99, and F1-score of 0.98. Furthermore, testing the model on various datasets revealed that the MobileNetV2 model had the best accuracy, at 0.94%. Our results show that the MobileNetV2 approach performs better in mpox picture classification than earlier models reported in the literature. These findings are encouraging because they demonstrate the potential of machine learning methods for mpox early diagnosis. In both the training and test sets, our system demonstrated a highdegree of accuracy in mpox classification, possibly making it a useful tool for prompt and precise diagnosis in clinical situations.**

I. INTRODUCTION

Monkeypox has been the subject of numerous local and international research and survey investigations COVID-19 pandemic. Information regarding the disease's clinical history, epidemiology, diagnosis, therapy, and preventative strategies are often the goals of these studies.

II. PROPOSED MODEL

The proposed approach showed the best performance, with accuracy of about 78%. Using MobileNet and smartphones developed a method for diagnosing skin diseases reported an accuracy of 94.4% when identifying individuals with chickenpox symptoms deep learning models and achieved 99.1% accuracy demonstrated that skin illness may be recognized 71% of the time applying image analysis with an already-existing VGG16. The proposed technique exhibited the best performance, with accuracy of roughly 78%. A technique for identifying skin conditions was created using MobileNet and smartphones. They found that 94.4% of those with chickenpox symptoms could be identified.

III. PROPOSED METHODOLOGY

Fig 3.1: The input image is first fed into two parallel branches of the procedure. The first uses Wavelet decomposition and Local Binary Pattern (LBP) to extract handcrafted texture features, while the second uses DenseNet-121 to derive deep CNN features. These CNN features are then subjected to an attention mechanism that highlights salient regions, and they are then multiplied element-wise with attention weights before being fused with the texture features via addition. The final classification output is produced by processing the combined feature map through a 1×1 convolution, global average pooling, and a fully connected layer.

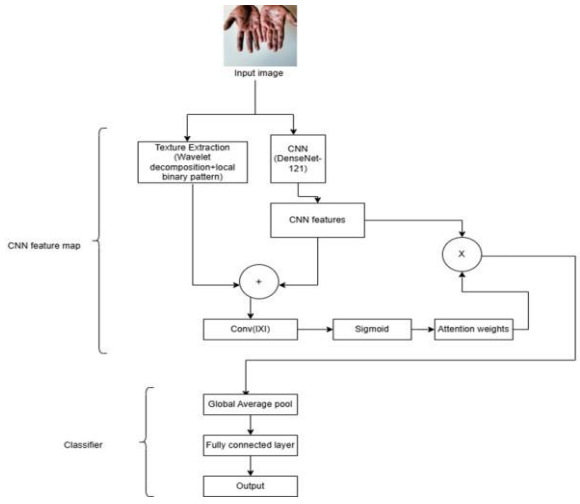

Fig 1: Architecture Diagram for Monkeypox Classification

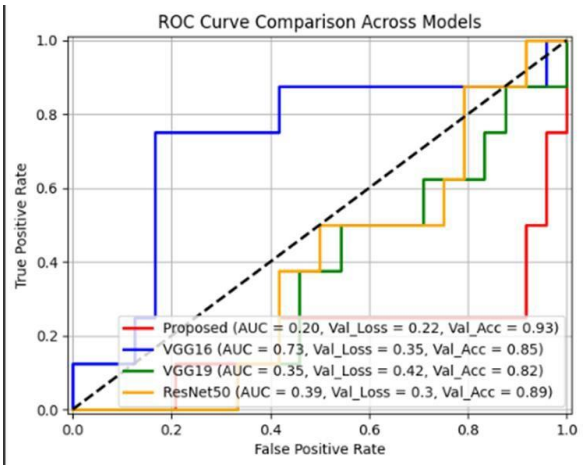

Fig 2 ROC curve comparison across models (Proposed in red, VGG16 in blue, VGG19 in green, ResNet50 in orange) Proposed model achieving the highest AUC (0.20), lowest validation loss (0.22), and highest validation accuracy (0.93), while VGG16 (AUC 0.73, val_loss 0.35, val_acc 0.85), VGG19 (AUC 0.35, val_loss 0.42, val_acc 0.82), and ResNet50 (AUC 0.39, val_loss 0.3, val_acc 0.89)

IV. CONCLUSION

The Logistic Regression machine learning model in conjunction with the MobileNet deep learning model yields very good results: accuracy is 0.97, precision is 0.99, recall is 0.98, and F1-score is 0.98. These discoveries aid in the creation of quick and precise diagnostic instruments, enhancing monkeypox early detection and diagnosis to reduce the disease's detrimental effects on public health. Better diagnostics can also improve patient outcomes, strengthen global health security in impacted countries, and increase the precision of this suggested approach. The accurate identification of the sick areas will be made easier with this improvement. Given the similarities between the skin lesions that are specific to chickenpox, monkeypox, and skin cancer, future research can focus on creating a CNN model that can correctly categorize these conditions. Another strategy might be to identify text data, like clinical notes or medical reports, as either unrelated to or linked to monkeypox using deep learning.

REFERENCES

[1]. Alakus TB, Baykara M. Comparison of Monkeypox and wart DNA sequences with deep learning model. Applied Sciences. 2022 Oct 11;12(20):10216

[2]. Abdelhamid AA, El-Kenawy ES, Khodadadi N, Mirjalili S, Khafaga DS, Alharbi AH, Ibrahim A, Eid MM, Saber M. Classification of monkeypox images based on transfer learning and the Al-Biruni Earth Radius Optimization algorithm. Mathematics. 2022 Oct 2;10(19):3614.

[3]. Jaradat AS, Al Mamlook RE, Almakayeel N, Alharbe N, Almuflih AS, Nasayreh A, Gharaibeh H, Gharaibeh M, Gharaibeh A, Bzizi H. Automated monkeypox skin lesion detection using deep learning and transfer learning techniques. International Journal of Environmental Research and Public Health. 2023 Mar 1;20(5):4422.

[4]. Uzun Ozsahin D, Mustapha MT, Uzun B, Duwa B, Ozsahin I. Computer-aided detection and classification of monkeypox and chickenpox lesion in human subjects using deep learning framework. Diagnostics. 2023 Jan 12;13(2):292.

[5]. Ahsan MM, Ali MS, Hassan MM, Abdullah TA, Gupta KD, Bagci U, Kaushal C, Soliman NF. Monkeypox diagnosis with interpretable deep learning. IEEE Access. 2023 Aug 1;11:81965-80.

[6].Altindis M, Puca E, Shapo L. Diagnosis of monkeypox virus–An overview. Travel medicine and infectious disease. 2022 Nov 1;50:102459.

[7]. Thornhill JP, Barkati S, Walmsley S, Rockstroh J, Antinori A, Harrison LB, Palich R, Nori A, Reeves I, Habibi MS, Apea V. Monkeypox virus infection in humans across 16 countries—April–June 2022. New England Journal of Medicine. 2022 Aug 25;387(8):679-91.

[8]. Gong Q, Wang C, Chuai X, Chiu S. Monkeypox virus: a re-emergent threat to humans. Virologica Sinica. 2022 Aug 1;37(4):477-82.

[9]. Alakunle E, Moens U, Nchinda G, Okeke MI. Monkeypox virus in Nigeria: infection biology, epidemiology, and evolution. Viruses. 2020 Nov 5;12(11):1257.

[10]. Moore MJ, Rathish B, Zahra F. Mpox (monkeypox). InStatPearls [Internet] 2023 May 3. StatPearls Publishing.

[11]. Mustapha, M.; Ozsahin, D.; Ozsahin, I.; Uzun, B. Breast Cancer Screening Based on

Supervised Learning and Multi-Criteria Decision-Making. *Diagnostics* **2022**, *12*, 1326.
[12]. Ozsahin, D.; Taiwo Mustapha, M.; Mubarak, A.; Said Ameen, Z.; Uzun, B. Impact of Feature Scaling on Machine Learning Models for The Diagnosis of Diabetes. In Proceedings of the 2022 International Conference on Artificial Intelligence in Everything (AIE), Lefkosa, Cyprus, 2–4 August 2022
[13]. Ozsahin, D.; Taiwo Mustapha, M.; Mubarak, A.; Said Ameen, Z.; Uzun, B. Impact of Feature Scaling on Machine Learning Models for The Diagnosis of Diabetes. In Proceedings of the 2022 International Conference on Artificial Intelligence in Everything (AIE), Lefkosa, Cyprus, 2–4 August 2022
[14]. Seang, S.; Burrel, S.; Todesco, E.; Leducq, V.; Monsel, G.; Le Pluart, D.; Cordevant, C.; Pourcher, V.; Palich, R. Evidence of Human-To-Dog Transmission of Monkeypox Virus. Lancet 2022, 400, 658–659.
[15]. Miura, F.; van Ewijk, C.; Backer, J.; Xiridou, M.; Franz, E.; Op de Coul, E.; Brandwagt, D.; van Cleef, B.; van Rijckevorsel, G.; Swaan, C.; et al. Estimated Incubation Period for Monkeypox Cases Confirmed in The Netherlands, May 2022. Eurosurveillance 2022, 27, 2200448.