Detection and prediction of monkey pox disease by enhanced convolutional neural network approach

Shaik Mazhar Hussain[1], Syed Ghouse[2]
[1]Centre for Research and Consultancy, Department of Computing and Electronic Engineering, Middle East College, Al Rusayl, Oman
[2]Department of Computer Science and Information Technology (CSIT), Jawaharlalnehru Technological University Hyderabad (JNTUH), Hyderabad, India

Article Info

Article history:

Received Aug 4, 2022
Revised Feb 21, 2023
Accepted Mar 10, 2023

Keywords:

Accuracy
Enhanced convolutional neural network model (E-CNN)
F1-Score
Modified visual geometry group (VGG) model
Monkeypox
Precision
Recall

ABSTRACT

Monkeypox is an infectious viral disease affecting both humans and animals. All symptoms are accompanied by a fever, swollen lymph nodes, and a rash that blisters before crusting. The interval between exposure and the development of symptoms is 5 to 21 days. Typically, symptoms last between two and four weeks. Although it is unknown to what degree it can happen without any signs. It has been found that not all outbreaks display the typical symptoms of fever, aches in the muscles, enlarged glands, and lesions appearing simultaneously. Cases may be severe, especially in children, pregnant women, or people with compromised immune systems. The problem can be detected and monitored at the early stages using some engineering solutions. Therefore, there is a necessity to develop accurate machine learning models for accurate interpretation before applying them in clinical trials. Hence, the proposed work has developed a model to diagnose monkey pox at the best accurate levels for accurate interpretation. The proposed enhanced convolutional neural network model is compared with the exisiting approaches. The obtained results were compared and indicate the superiority of the proposed algorithm.

Corresponding Author:

Shaik Mazhar Hussain
Centre for Research and Consultancy, Department of Computing and Electronic Engineering,
Middle East College
Rusayl, Oman
Email: mazhar@mec.edu.om

1. INTRODUCTION

Monkeypox had first been identified in 1958 as an outcome of two outbreaks of a condition resembling the pox in colonies of monkeys held for research. Although the illness is known as "monkeypox," its origin is still unknown. However, the virus has the potential to infect humans via African rodents and other animals (such as monkeys). In 1970, there was the first known incidence of monkeypox in humans [1]. Monkeypox cases have now been documented in several additional central and western African nations. Nearly all instances of monkeypox in people outside of Africa prior to the 2022 pandemic were linked to either imported animals or international travel to countries where the disease frequently occurs. Monkeypox is a rare condition caused by infection with the monkeypox virus. The monkeypox virus is found in the orthopoxvirus genus and family Poxviridae [2]– [6]. Monkeypox and chicken pox are unrelated. Early indications of monkeypox include shivering, high fever, headache, muscular pains, and backaches (chills). exhaustion. Furthermore, the second stage of symptoms, which includes the following, will appear within one to three days. Sometimes, people first get a rash before experiencing additional symptoms. Others only experience a rash [7]. Animal-to-person transmission happens when the skin is injured, such as via bites or scratches, or when an infected animal's blood, body fluids, or pox lesions are directly touched (sores). Initial observations of the peculiar characteristics of any skin lesions present, as well as any past exposure history, are part of the process for diagnosing monkeypox. Electron microscopy testing on skin lesions, however, is the only guaranteed technique to identify the virus. Additionally, a polymerase chain reaction can be used to validate the monkeypox virus. It is presently widely utilized in the diagnosis of COVID-19 patients. In numerous disciplines, safe, accurate, and quick imaging solutions can be achieved using machine learning (ML), an emerging topic of artificial intelligence (AI). These solutions have acquired widespread recognition as useful decision-making tools [8]–[13].

To date, the monkeypox outbreak has infected over 15,000 people in over 70 countries, including over 2,300 in the United States [14]. Priorities for monkeypox research will thus enable us to understand better about the virus and what will work best to halt the outbreak. The priorities will also serve as a guide for the global scientific community. The following are critical in addressing the problem of monkey pox disease: i) our understanding of the transmission dynamics of monkeypox, epidemiology, and clinical features of the disease; ii) novel approaches to testing monkeypox engineering solutions. hence, there is a necessity to develop ai techniques for the prediction analysis of monkeypox; iii) country perspectives on research priorities and opportunities.

We attempt to highlight state-of-the-art findings and investigate the performance metrics that have been used to assess the performance of existing approaches [15], used a variety of segmentation techniques to find skin problems such as chicken pox, candidiasis, cellulitis, and acne. A low-complexity convolutional neural network (CNN) is presented to recognize skin conditions like chicken pox, psoriasis, melanoma, and lupus [16], They demonstrate 71% accuracy in the detection of skin illness utilizing the existing visual geometry group deep convolutional neural network (VGGNet). Their suggested solution, in contrast, achieves the best outcomes by obtaining an accuracy of about 78% [17], 108 patients with COVID-19 and 86 patients without it were included in a small dataset for the evaluation of ten different deep-learning models, and the accuracy rate was 99%. Ahsan *et al.* [18]. Proposed a smartphone-based method for identifying skin diseases using Mobile Net and reported a 94.4% success rate in identifying individuals with chicken pox symptoms. Miranda and Felipe [19] created fuzzy logic computer-aided diagnostic (CAD) systems to identify breast cancer. The technical contribution of the proposed work includes: i) developing an image dataset from the images; ii) feature extraction, classification, and prediction of monkey pox disease by Enhanced CNN model.

2. RESEARCH METHOD

A convolutional neural network with 16 layers is called VGG-16. A ConvNet is another name for a convolutional neural network, which is a type of artificial neural network. An input layer, an output layer, and many hidden layers make up a convolutional neural network. The 13 convolutions, 5 max pooling, and 3 dense layers make up this model. Because it includes 16 layers with learnable weight parameters, it is known as VGG-16. A dataset of images depicting the monkeypox is used in this article. Our proposed work is mainly focused on developing a mechanism to diagnose people infected with monkey pox disease by an enhanced convolutional neural network model. Further, the proposed algorithm is compared with the existing approaches. There are various sub-folders in the dataset, including ones for datasets with and without augmentations. We employ enhanced photos in this work because DL models favor them and can more accurately acquire important information from them. The performance metrics that are evaluated in this work are accuracy, precision, recall, F1-score, sensitivity, and specificity. This section briefs the method used and the parameters evaluated. In this paper, as an example, we try to design the existing approach called transfer learning modified VGG-16 and enhanced CNN algorithm to predict monkeypox disease. In addition, the other approaches will be evaluated accordingly. To train both the algorithms, we used normal skin and monkeypox images. Figure 1 shows the main steps used in the proposed method and the data for the monkeypox image is gathered from a variety of sources. To do this, the initial search is conducted using the Google search engine.

The following modules have been designed to implement the work: i) upload monkeypox dataset: Using this module, we will upload the dataset to the application; ii) preprocess dataset: Using this module, we will read all images and then resize images to equal size and then normalize image pixel values, and then split the entire dataset into Train and Test, where the application user has 80% images for training and 20% for testing. The 20% of test images will be applied to the trained model to calculate correct prediction accuracy; iii) run VGG-16 Algorithm: Above processed 80% of images will be input to the VGG algorithm to train the prediction model and this model will be applied don test images to calculate prediction accuracy; iv) run Enhanced CNN Algorithm: Above processed 80% of images will be input to the Enhanced CNN algorithm to train the prediction model and this model will be applied don test images to calculate prediction accuracy; v) Comparison Graph: Using this module we will plot comparison graph between VGG and Enhanced CNN algorithms. The evaluation of the other three algorithms will be shown in the Table 1; vi) prediction of disease from the test image: Using this module we will upload a test image and then Enhanced CNN will predict weather the image is normal or contains Monkeypox disease. Table 1 gives the comparision of VGG-16 model, ResNet50, InceptionV3, Ensemble, Modified VGG-16, and Enhanced Convolutional Neural Network Model in terms of accuracy, precision, recall, and F1-score.

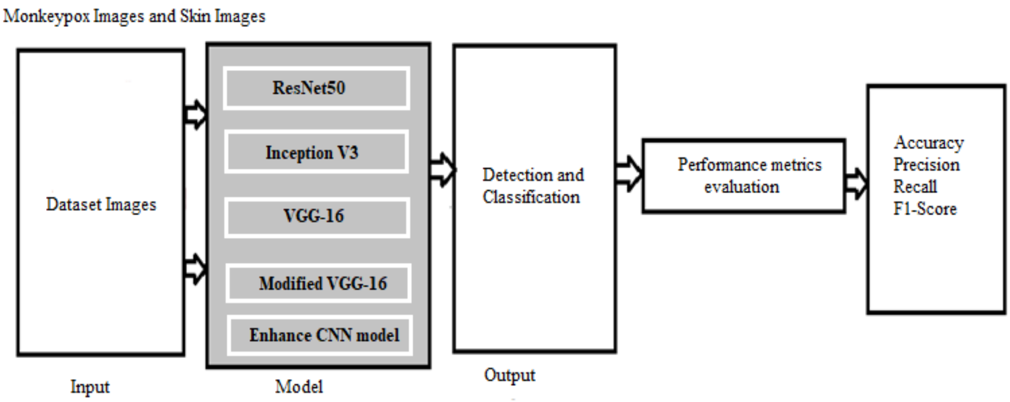

Figure 1. Steps followed in our proposed work

Table 1. Comparision of the performance metrics for the existing approaches and enhanced convolutional neural network model

Algorithms	Accuracy	Precision	Recall	F1-Score
Modified VGG-16 [20], [21]	98.24561403508771	98.22967980295567	98.27426810477658	98.24439824439824
ResNet50 [22]	82.96	87	83	84
InceptionV3 [22]	74.07	74	81	78
Ensemble [22]	79.26	84	79	81
VGG16 [21]	81.48	85	81	83
Enhanced CNN Model	99.12280701754386	99.10714285714286	99.15254237288136	99.12219912219912

3. RESULTS AND DISCUSSION

In this section, we discuss the comparative analysis of VGG-16 model, ResNet50, InceptionV3, Ensemble, Modified VGG-16 with our proposed approach. We evaluated the performance of the selected pre-trained models. The obtained results are summarized in Table 1. While ResNet50 yields the best accuracy 82.96%, VGG16 shows competitive performance 81.48%. We also use majority voting to implement an ensemble of the three models. The ensemble model did not outperform the best performing ResNet50 model. However, the ensemble system has the lowest accuracy metric standard deviation, indicating that its performance is more consistent across the three folds. Further evaluation is carried out using the most recent existing approach known as the modified VGG-16 model. The proposed enhanced CNN model was used to analyze all the previous approaches. To demonstrate the superiority of our proposed method, it is compared to the existing VGG-16 model, ResNet50, InceptionV3, Ensemble, Modified VGG-16. The algorithms' performance is analyzed and evaluated using the following metrics: accuracy, precision, recall, F score, Specificity, and Sensitivity. Specificity and sensitivity are important metrics in medical imaging for assessing classifier completeness.

3.1. Experimental Setup

The experimental setup and library packages are shown in Table 2 [23]–[30].The overall experiment was repeated five times, and the result was obtained by averaging the five computational outcomes. Figures shown below are the steps to analyse the performance of VGG-16 and Enhanced CNN model. Figure 2 shown is the Double-click the "run.bat" file to launch the project. To upload the dataset, select the "Upload Monkeypox Dataset" button on the screen. After loading the dataset, choose "Preprocess Dataset" to read and process all the photos as shown in Figure 3.

Table 2. Computer system specifications for the proposed work

Computer	Specifications
Dell Latitude E5450	System requirement: Minimum size of Random Access Memory (RAM) is 4 gigabytes, 64-bit OS windows, python 3.7.0\ Library packages: pip install pandas ==0.25.3 pip install matplotlib ==3.1.1 pip install numpy == 1.19.2 pip install scikit-learn ==0.22.2. post1 pip install nltk ==3.4.5 Processor: Intel(R) Core (TM) i5-5200U CPU @ 2.20GHz 2.19 GHz

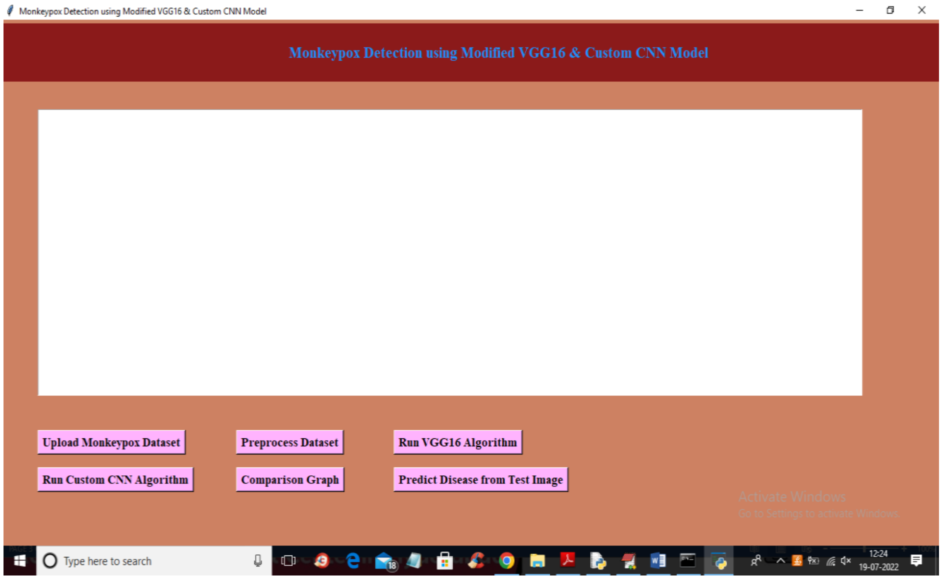

Figure 2. Upload monkeypox dataset

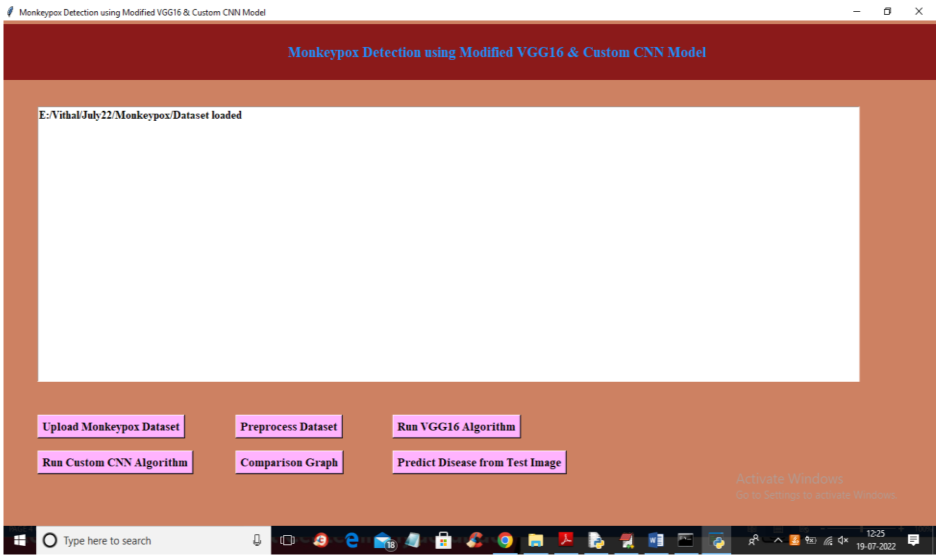

Figure 3. Preprocess dataset

Figure 4 shows the dataset is loaded and now click on the 'Preprocess Dataset' button to read all images and then processed them. We can see all images read and then processed and we can see the dataset contains a total of 1139 images and applications using 911 (80%) images for training and 228 (20%) images for testing and to check all images are processed properly. Here, one sample image is displayed now close that image and then click on the 'Run VGG16 Algorithm' button to train VGG.

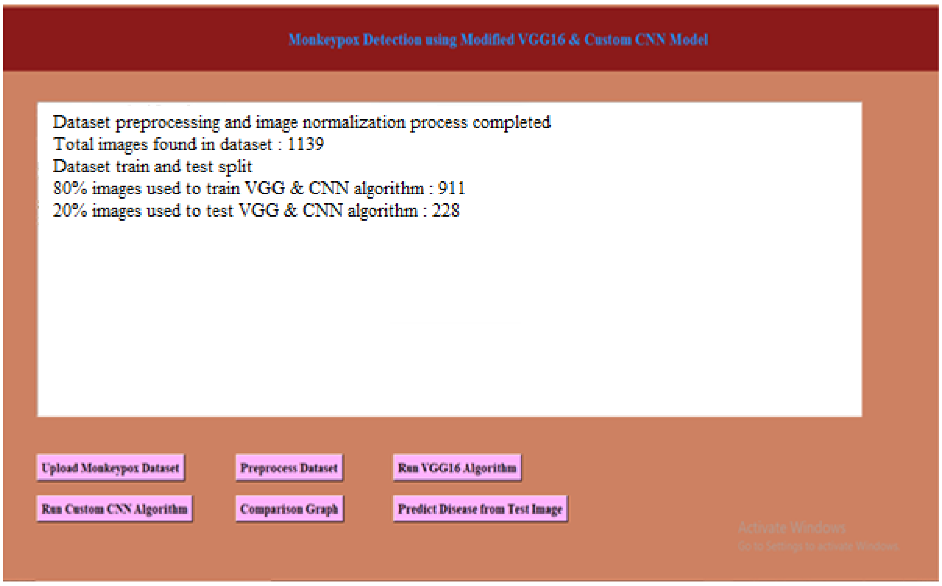

Figure 4. Run VGG16 algorithm

3.2.2. Comparision of exisiting modifed VGG 16 model and enhanced convolutional neural network model.

A comparison of the accuracy, precision, recall, F-score, sensitivity, and specificity for the VGG model and Proposed model is shown in Table 1. The results obtained in Table 1 clearly show the superiority of the proposed algorithm as compared to the existing approach. To train both algorithms, we used normal skin images and monkeypox images. The results show that the proposed CNN model is superior, with a 99.12% accuracy, 99.10% precision, 99.15% recall, 99.12% F-score, improvement in sensitivity to about 99.21%, and specificity to about 99.18%. Figure 5 shows the modified VGG16 Confusion matrix where we have achieved 98.24% accuracy and we can see other metric values also. In the confusion matrix graph, the x-axis represents predicted classes, and the y-axis represents true classes we can predict in matching row and column name is correct and un-matched rows and columns names are incorrect prediction in the above graph we can see VGG16 predicted 1 and 3 (total 4 images) incorrectly and now 'Run Enhanced CNN Algorithm' button to train.

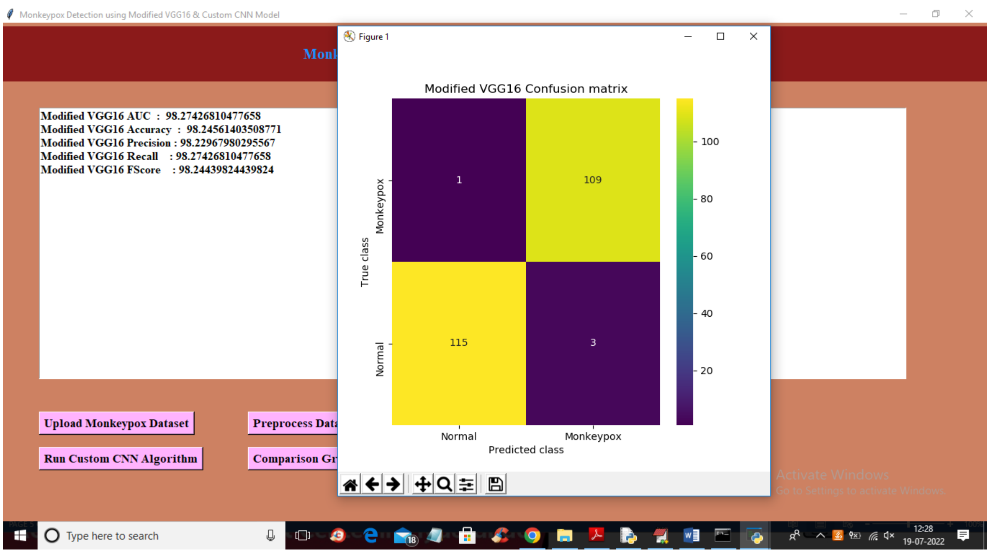

Figure 5. Modified VGG16 confusion matrix

Figure 6 shows the Enhanced CNN Confusion matrix. Clearle, we have achieved 99.12% accuracy. In the confusion matrix graph, we can see only two images are incorrectly predicted now close the above graph and then click on the ‘Comparison Graph’ button.

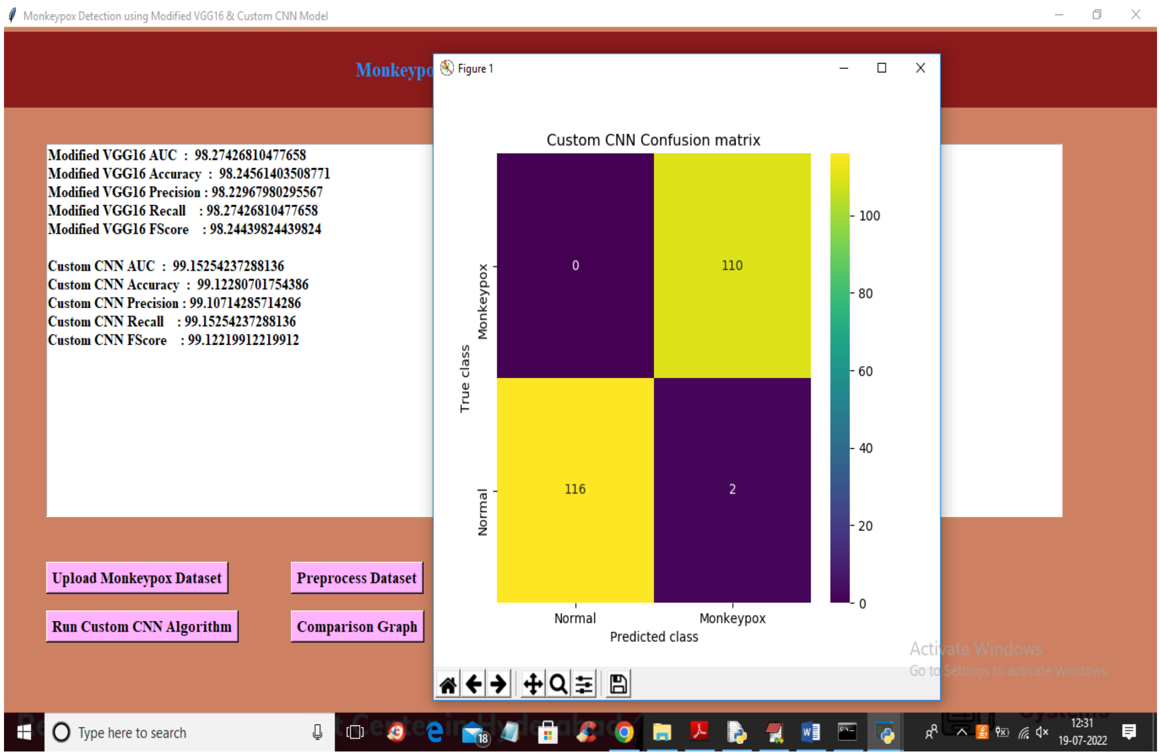

Figure 6. Enhanced CNN confusion matrix

Figure 7 shows the tabular format and graph format. We can see the result of both algorithms and now go back to the main application and then click on the ‘Predict Disease from Test Image’ button to upload the test image and get the below output. Hence, Figures 8 and 9 classify the detection of monkey pox.

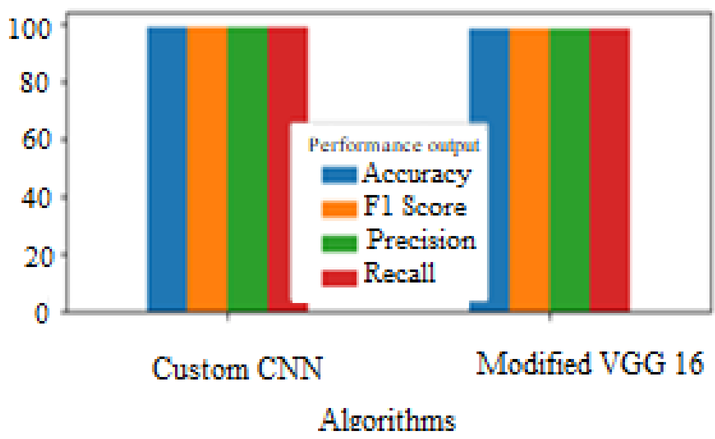

Figure 7. Performance output

Figure 8. Detection of monkeypox

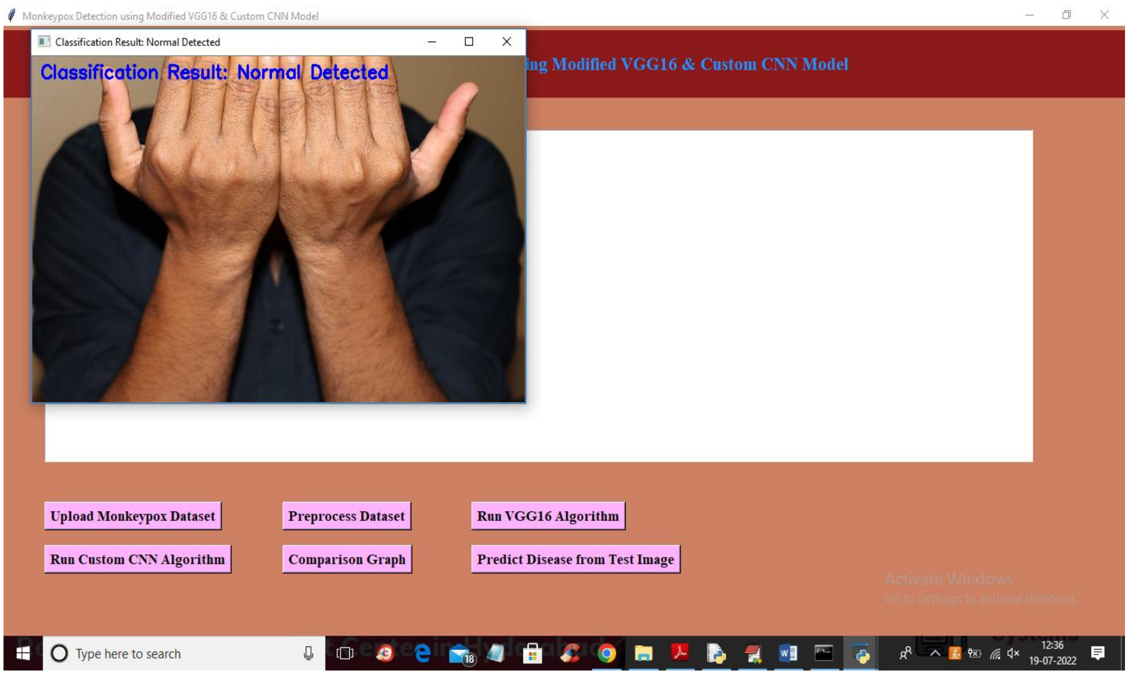

Figure 9. Normal detection

4. CONCLUSION

The article's objective is to address ongoing concerns about the monkeypox virus. In this study, we proposed an improved CNN model to classify monkeypox disease and compared it to state-of-the-art deep learning architectures using the transfer learning approaches (VGG-16, ResNet50, InceptionV3, modified VGG-16 model). Further, the performance of the proposed model is evaluated to check its ability to distinguish patients with and without monkeypox disease. The results have shown a greater improvement in the performance metrics for predicting monkeypox. Future work can be extended by upgrading the dataset by regularly gathering new images of monkeypox-infected patients.

ACKNOWLEDGEMENTS

I would like to acknowledge Middle East College, Muscat, Oman for their unceasing support and for enhancing research facilities to complete this research work successfully.

REFERENCES

[1] A. M. McCollum and I. K. Damon, "Erratum: human monkeypox (clinical infectious diseases (2013) 58 (260-267))," *Clinical Infectious Diseases*, vol. 58, no. 12, p. 1792, Jun. 2014, doi: 10.1093/cid/ciu254.

[2] E. Alakunle, U. Moens, G. Nchinda, and M. I. Okeke, "Monkeypox virus in nigeria: infection biology, epidemiology, and evolution," *Viruses*, vol. 12, no. 11, p. 1257, Nov. 2020, doi: 10.3390/v12111257.

[3] L. D. Nolen *et al.*, "Extended human-to-human transmission during a monkeypox outbreak in the democratic republic of the congo," *Emerg Infect Dis*, vol. 22, no. 6, pp. 1014–1021, Jun. 2016, doi: 10.3201/eid2206.150579.

[4] P.-Y. Nguyen, W. S. Ajisegiri, V. Costantino, A. A. Chughtai, and C. R. MacIntyre, "Reemergence of Human Monkeypox and Declining Population Immunity in the Context of Urbanization, Nigeria, 2017–2020," *Emerg Infect Dis*, vol. 27, no. 4, Apr. 2021, doi: 10.3201/eid2704.203569.

[5] F. Mustaffa, N. A. Zaini, and K. Selvarajah, "Review: an analysis of monkeypox disease and current scenario in Malaysia," *International Journal of Research -granthaalayah*, vol. 7, no. 9, pp. 82–87, Sep. 2019, doi: 10.29121/granthaalayah. v7.i9.2019.562.

[6] S. K. Smith, V. A. Olson, K. L. Karem, R. Jordan, D. E. Hruby, and I. K. Damon, "In Vitro Efficacy of ST246 against Smallpox and Monkeypox," *Antimicrob Agents Chemother*, vol. 53, no. 3, pp. 1007–1012, Mar. 2009, doi: 10.1128/AAC.01044-08.

[7] A. J. Georges and M. C. Georges-Courbot, "Biohazards due to Orthopoxvirus: should we re-vaccinate against smallpox?," *Med Trop (Mars)*, vol. 59, no. 4 Pt 2, pp. 483–487, 1999.

[8] W. S. Ahmed and A. amir A. Karim, "The impact of filter size and number of filters on classification accuracy in CNN," in *2020 International Conference on Computer Science and Software Engineering (CSASE)*, Apr. 2020, pp. 88–93. doi: 10.1109/CSASE48920.2020.9142089.

[9] H. Qassim, A. Verma, and D. Feinzimer, "Compressed residual-VGG16 CNN model for big data places image recognition," in *2018 IEEE 8th Annual Computing and Communication Workshop and Conference (CCWC)*, Jan. 2018, pp. 169–175. doi: 10.1109/CCWC.2018.8301729.

[10] Z. Mushtaq, S.-F. Su, and Q.-V. Tran, "Spectral images based environmental sound classification using CNN with meaningful data augmentation," *Applied Acoustics*, vol. 172, p. 107581, Jan. 2021, doi: 10.1016/j.apacoust.2020.107581.

[11] K. Roy, S. S. Chaudhuri, S. Ghosh, S. K. Dutta, P. Chakraborty, and R. Sarkar, "Skin Disease detection based on different Segmentation Techniques," in *2019 International Conference on Opto-Electronics and Applied Optics (Optronix)*, Mar. 2019, pp. 1–5. doi: 10.1109/OPTRONIX.2019.8862403.

[12] S. J. S. Rajasekar, "An enhanced IoT based tracing and tracking model for COVID -19 Cases," *SN Comput Sci*, vol. 2, no. 1, p. 42, Feb. 2021, doi: 10.1007/s42979-020-00400-y.

[13] Z. bin S. Al Brashdi, S. M. Hussain, K. M. Yosof, S. A. Hussain, and A. V. Singh, "IoT based health monitoring system for critical patients and communication through think speak cloud platform," in *2018 7th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO)*, Aug. 2018, pp. 652–658. doi: 10.1109/ICRITO.2018.8748751.

[14] T. Kitamura, "Monkeypox virus diseases in humans," *Uirusu*, vol. 34, no. 2, pp. 89–97, 1984, doi: 10.2222/jsv.34.89.

[15] F. Q. Jin, M. Postiglione, A. E. Knight, A. R. Cardones, K. R. Nightingale and M. L. Palmeri, "Comparison of Deep Learning and Classical Image Processing for Skin Segmentation," *2019 IEEE International Ultrasonics Symposium (IUS)*, Glasgow, UK, 2019, pp. 1152-1155, doi: 10.1109/ULTSYM.2019.8926233.

[16] T. Qiu, C. Wen, K. Xie, F. Wen, G. Sheng, and X. Tang, "Efficient medical image enhancement based on CNN-FBB model," *IET Image Process*, vol. 13, no. 10, pp. 1736–1744, Aug. 2019, doi: 10.1049/iet-ipr.2018.6380.

[17] A. A. Ardakani, A. R. Kanafi, U. R. Acharya, N. Khadem, and A. Mohammadi, "Application of deep learning technique to manage COVID-19 in routine clinical practice using CT images: Results of 10 convolutional neural networks," *Comput Biol Med*, vol. 121, p. 103795, Jun. 2020, doi: 10.1016/j.compbiomed.2020.103795.

[18] M. M. Ahsan, R. Nazim, Z. Siddique, and P. Huebner, "Detection of COVID-19 Patients from CT Scan and Chest X-ray Data Using Modified MobileNetV2 and LIME," *Healthcare*, vol. 9, no. 9, p. 1099, Aug. 2021, doi: 10.3390/healthcare9091099.

[19] G. H. B. Miranda and J. C. Felipe, "Computer-aided diagnosis system based on fuzzy logic for breast cancer categorization," *Comput Biol Med*, vol. 64, pp. 334–346, Sep. 2015, doi: 10.1016/j.compbiomed.2014.10.006.

[20] N. Tang, H. Liu, K. Yue, W. Li, and X. Yue, "Automatic classification for corneal ulcer using a modified VGG network," *2020 International Conference on Artificial Intelligence and Computer Engineering (ICAICE)*, Beijing, China, 2020, pp. 120-123, doi: 10.1109/ICAICE51518.2020.00029.

[21] H. Qassim, A. Verma, and D. Feinzimer, "Compressed residual-VGG16 CNN model for big data places image recognition," in *2018 IEEE 8th Annual Computing and Communication Workshop and Conference (CCWC)*, Jan. 2018, pp. 169–175. doi: 10.1109/CCWC.2018.8301729.

[22] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, "Rethinking the Inception Architecture for Computer Vision," in *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Jun. 2016, pp. 2818–2826. doi: 10.1109/CVPR.2016.308.

[23] A. Narin, C. Kaya, and Z. Pamuk, "Automatic detection of coronavirus disease (COVID-19) using X-ray images and deep convolutional neural networks," *Pattern Analysis and Applications*, vol. 24, no. 3, pp. 1207–1220, Aug. 2021, doi: 10.1007/s10044-021-00984-y.

[24] E. M. Bunge *et al.*, "The changing epidemiology of human monkeypox—A potential threat? A systematic review," *PLoS Negl Trop Dis*, vol. 16, no. 2, p. e0010141, Feb. 2022, doi: 10.1371/journal.pntd.0010141.

[25] A. Vaughan *et al.*, "Human-to-Human Transmission of Monkeypox Virus, United Kingdom, October 2018," *Emerg Infect Dis*, vol. 26, no. 4, pp. 782–785, Apr. 2020, doi: 10.3201/eid2604.191164.

[26] D. Ravi *et al.*, "Deep Learning for Health Informatics," *IEEE J Biomed Health Inform*, vol. 21, no. 1, pp. 4–21, Jan. 2017, doi: 10.1109/JBHI.2016.2636665.

[27] G. H.-J. Kwak and P. Hui, "DeepHealth: Deep Learning for Health Informatics," *ArXiv*, 2019.

[28] B. Shickel, P. J. Tighe, A. Bihorac and P. Rashidi, "Deep EHR: A Survey of Recent Advances in Deep Learning Techniques for Electronic Health Record (EHR) Analysis," in *IEEE Journal of Biomedical and Health Informatics*, vol. 22, no. 5, pp. 1589-1604, Sept. 2018, doi: 10.1109/JBHI.2017.2767063.

[29] S. Huggi and S. Jamuna, "Design and Verification of Memory Elements using Python," in *Proceedings of CONECCT 2020 - 6th IEEE International Conference on Electronics, Computing and Communication Technologies*, 2020. doi: 10.1109/CONECCT50063.2020.9198470.
[30] Z. Ahmed, F. J. Kinjol, and I. J. Ananya, "Comparative Analysis of Six Programming Languages Based on Readability, Writability, and Reliability," in *24th International Conference on Computer and Information Technology, ICCIT 2021*, 2021. doi: 10.1109/ICCIT54785.2021.9689813.

BIOGRAPHIES OF AUTHORS

Shaik Mazhar Hussain Department of Electronics and Communications Engineering received his bachelor and master's degree in Electronics and Communication Engineering from JNTU, Hyderabad, India in 2008 and 2012 respectively, and received PGCert from Coventry University, UK in December 2017, Ph.D. from Universiti Teknologi Malaysia (UTM), Johor Bahru, Malaysia, 2022. His research areas of interest include Wireless Communications, Internet of Vehicles (IoV), and Intelligent Transportation System (ITS). He can be contacted at email: mazhar@mec.edu.om.

Syed Ghouse Department of Information Technology, received his bachelor's degree in Information Technology (IT) from JNTU, Hyderbad, India and received his master's degree in Information Technology (IT) from JNTU, Hyderbad, India. His research areas of interests include Wireless mobile communication systems, Network routing protocols (RIP, IGP, EIGRP, OSPF & BGP), Intelligent Transportation System (ITS) and Internet of Things (IoT). He can be contacted at email: isyedghouse@gmail.com.