Distinguishing Monkeypox from Common Skin Lesions using Artificial Intelligence in a Sexual Health Clinic: A Feasibility Study

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Background:
The 2022 global monkeypox (Mpox) outbreak like other sexually transmitted infections (STIs) is best controlled through early recognition and access to healthcare. Healthcare services for STIs are at capacity and so other ways of assisting the public with the diagnosis could improve control. Our study aims to develop an AI-assisted diagnosis tool for differentiating Mpox from other common STI/non-STI skin lesions in a sexual health clinic setting.

Methods:
We used the existing lesion images recorded at Melbourne Sexual Health Centre (MSHC). MSHC dataset included a total of 1,922 (357 Mpox and 1565 non-Mpox lesions), of which 80% used for model training and 20% for testing). Non-Mpox lesion images included common STIs (genital warts, herpes, syphilis, molluscum contagiosum, monkeypox, gonorrhea) and non-STIs (healthy skin, pearly white penile papules, vaginal intraepithelial neoplasia (VIN), balanitis, lichen sclerosis and other dermatosis). We performed lesion alignment of images and used a residual convolutional neural network (6 types of pre-trained models) to learn coupled spatiotemporal features from aligned images. Then, we extracted the spatiotemporal features of the lesions to classify them into the respective Mpox in comparison with non-Mpox. We chose the best model with highest performance in MSHC dataset and evaluated the model's performance with publicly available Mpox dataset from Kaggle.

Results:
The DenseNet-V2 models trained with 150 epochs, and a $3e^{-4}$ learning rate, outperformed the other models in terms of overall AUC (0.928 ± 0.022), accuracy (0.848 ± 0.041), precision (0.942 ± 0.013), recall (0.742 ± 0.024) and F1-score (0.834 ± 0.018). Furthermore, we applied the region-of-interest approach, resulting in an even higher AUC of 0.982 ± 0.002) on the MSHC testing dataset. This model also achieved a similar AUC score of 0.982 ± 0.001 on the Kaggle dataset.

Conclusion:
The AI-assisted diagnostic tool could be integrated into existing healthcare platforms or made publically available for early detection of Mpox cases. This could improve the clinic workflow management and prevent transmission of Mpox infection. As a future work, further research is needed to improve the performance of the model and validate its effectiveness in real-world clinical settings.

Disclosure of interest Statement:
No conflict of interest declared.