An Effective Combination of Deep and Machine Learning Models for Monkeypox Detection from Dermatographic Image

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Abstract. The recent outbreak of monkeypox spread over seventy-six countries, seventy of them not having any prior history of monkeypox cases, because of its complex transmission patterns and high frequency of human-to-human transmission. As a result, it has appeared as one of the most critical health concerns. Therefore, a quick diagnosis is crucial, and in this case, computer-aided lesion detection may help identify suspected cases quickly. In this work, the first three pre-trained architectures, VGG19, ResNet-50, and DenseNet121, for the transfer learning approach. Among them, ResNet50 proved a comparatively ideal outcome and diagnostic validity arrived at 97.68%. Then, the system combines the in-depth features and machine learning classifiers to get more effective results. From the experimental outcomes, The research finds that the detection accuracy of ResNet50 + SVM is 99.55%, which is improved by 2.47% from the baseline ResNet50 model. In addition, our proposed system also achieves 99.82% sensitivity, 99.33% specificity, and 99.69% AUC, respectively. Therefore, This research shows that the introduced method can be a beneficial tool for clinical decision-making.

Keywords: Deep learning · machine learning · transfer · learning · monkeypox · classification

1 Introduction

Monkeypox, categorized as a zoonotic ailment, is a member of the Poxviridae family and falls under the Orthopoxvirus genus (OPV). Monkeypox is one of the five OPV species that are harmful to humans. It was first identified in 1958

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by the Statens Serum Institute in Denmark, and they named it Monkeypox [1]. The first human cases of the disease were first officially recognized in 1970 within the Democratic Republic of Congo. Monkeypox's symptoms include fever and headache, feeling tired and swollen glands. Some of the first symptoms might be flu, body aches, and then rash, which typically starts on the face before spreading to the other parts of the body [2]. It spreads from person to person through direct contact with individuals who are infected or through contact with objects that have been contaminated [3].

The recent outbreak in May 2022 of this viral disease, had highlighted the lack of knowledge of this viral disease. The WHO suggested people should maintain social distance so the spread of viral infection could be limited and prevented [2]. It is not likely that it will generate a significant transmission. But research cannot rule it out, so researchers have to be very careful. The WHO says the general public should be aware of unusual skin rashes. Although the case fatality ratio for the most recent epidemic has been estimated to be 3-6% [2], early detection of Monkeypox, thorough contact tracing, and isolation are crucial to stop the virus from spreading within communities. So, to stop the spreading, a proposed system must identify Monkeypox by differentiating it from others of the same family, for example, from smallpox. However, it is challenging for human beings without rigorous testing.

Up to this point, the most favored method, providing the highest accuracy and sensitivity, remains the laboratory-based Polymerase Chain Reaction (PCR) test [2]. However, computer-aided systems have demonstrated their effectiveness and speed in this regard. Therefore, they can be employed for rapid Monkeypox identification. Various CAD tools are available and capable of performing effectively, with deep learning (DL) and machine learning (ML) emerging as potentially the most efficient options for distinguishing Monkeypox from other poxviruses without the need for human intervention. Due to its advanced learning capabilities, deep learning (DL) has recently made significant strides in revolutionizing various fields of medical research[4,5,6,7,8]. These complex neural networks can assess images through multiple layers, autonomously identifying critical features and becoming proficient at selecting the most appropriate representations for specific tasks when trained with extensive datasets [9]. Transfer learning is another frequently employed technique, particularly in situations where data is limited [4].

With a view to detecting monkeypox by analyzing the dermatoscopic image of skin lesions, S. Nafisa Ali and their team propose a deep learning method where they employ several pre-trained CNN models [10]. They also utilize the data augmentation technique to increase sample size and apply a three-fold cross-validation method for training and testing a model. According to their result, their best model achieved 82.96($\pm$4.57%) accuracy. The accuracy can be further increased by applying different techniques like fine-tuning. In another paper [11] by M. Arafat Hussain et al. proposed a DL-based system to identify monkeypox from images, and they used seven DL models for their study. Their datasets contain more dermatoscopic pictures of skin lesions along with ox, measles, and healthy images. In their cases, they found 79% accuracy. Paper [12] from V.H Sahin and his team develop a system for Monkeypox classification from skin lesions. They propose to train their system with pre-trained CNN networks using the transfer learning method. According to their test results, the system can classify the skin lesion images with 91.11% accuracy. In this paper, The main objective is to develop a powerful combination of in-depth features and machine learning classification to aid the doctor in more effectively diagnosing Monkeypox. The significant contributions of this work are:

1. First, transfer learning is utilized to mitigate the overfitting issue that deep learning struggles through due to the scarcity of a huge training data set. The ImageNet dataset was used for pre-training three widely recognized CNN models, specifically VGG16, ResNet50, and DenseNet121. Also, their performance was verified for detecting the infected skin parts from the test set. Among them, ResNet50 has a 96.75% accuracy rate.
2. This research uses pre-trained deep learning models for automated feature extraction, replacing complex manual methods. Bottleneck features extracted from the images are then fed into various machine learning classifiers for efficient Monkeypox diagnosis.
3. The extensive test analysis shows that each deep model performs excellently on several classifiers. The top model has a 99.55% accuracy rate.

2 Methodology

2.1 Transfer learning and pre-trained model

A large dataset is sometimes difficult to gather in medical imaging. To produce superior results and avoid overfitting, deep learning models need a large number of labeled datasets [13]. To address these challenges, The system begins by employing a widely used technique: transfer learning. This method entails the utilization of a model that has previously been trained on a large labeled dataset for a different research project, as depicted in Fig 1. Given the substantial data demands and the impracticality of training a neural network from scratch due to constraints related to processing power and time, The research fine-tunes the parameters of the pre-trained deep learning network model to suit the requirements of the new task.

To adapt the system to the two-class dataset, the model was fine-tuned through specific adjustments. Firstly, the fully connected layer at the top of the pre-trained model was replaced with a custom one. Following this modification, the convolutional layers were frozen, allowing for focused training of the customized layer. The study evaluated three commonly used models: VGG19 [14], ResNet50 [15], and DenseNet121 [16]. The architecture of these models is outlined briefly below.

– VGG19, proposed by Simonyan and Zisserman [14], competed in the 2014 ImageNet Large Scale Visual Recognition Challenge (ILSVRC2014) and produced outstanding outcomes. It employs a smaller convolution kernel and

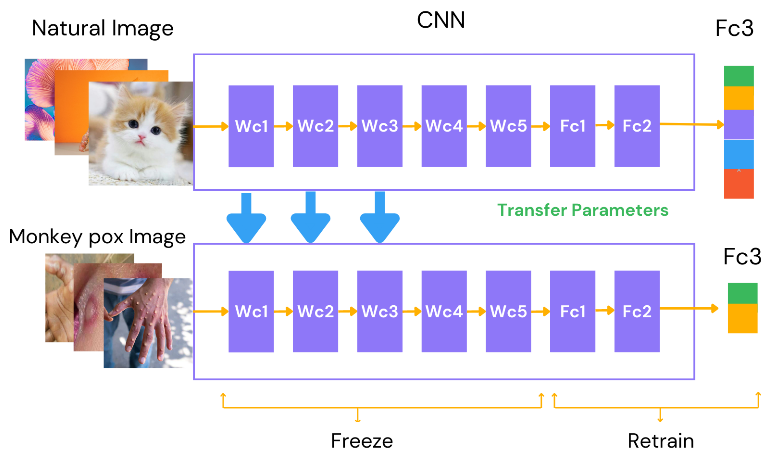

Fig. 1. Workflow of deep models for transfer learning and fine-tuning.

fewer parameters than AlexNet, and the classification impact is substantially better.

- ResNet50 is a convolutional neural network structure that has recently gained much popularity. It grabbed the first position in the 2015 ILSVRC competition. This model's inventively suggested residual design provides a more straightforward gradient flow and more efficient training [15].
- The most recent network configuration is DenseNet121. It is the ImageNet competition's 2017 champion. With fewer parameters, it produces outstanding results by using features. When maximal information transfer between network levels is guaranteed, it can link all layers directly [16].

2.2 Proposed method

The proposed method introduces an approach for automatically identifying monkeypox in skin lesion pictures by combining deep features and machine-learning classification strategies. The methodology proposed for detecting monkeypox operates through multiple stages, as detailed in Fig 2.

First Phase: Preprocessing of raw images: The raw images are preprocessed in this phase to boost the CNN architecture's ability to generalize. When training the deep learning model, only two common preprocessing steps and data augmentation techniques are used, as described below:

- Rescale and Normalization: Since images in the dataset might come from various devices and sources, their acquisition settings and pixel sizes can vary significantly. To ensure consistent processing and training, all images are rescaled to a standard size of 224 x 224 pixels. This ensures compatibility

with the chosen pre-trained model and simplifies further processing steps. Additionally, all image data is normalized to set the intensity values between [-1, 1].
- Data augmentation: To address overfitting risk arising from limited training data, especially when dealing with deep network architectures, various augmentation techniques such as shear, hue adjustments, saturation modifications, contrast variations, brightness adjustments, noise addition, and scaling were implemented. These techniques artificially increase the size and diversity of the training data, allowing the model to learn more generalizable features.

Second Phase: Extracting Features Using Pre-Trained Deep Learning Models: Pre-trained deep learning systems are used to drag bottleneck features. The performance of the transfer learning with fine-tuning strategy in this task is not notable. Therefore, an alternative representation approach for convolutional features is proposed to enhance the model's performance and generalizability. As feature extractors, three pre-trained CNN architectures (VGG16, ResNet50, and DenseNet121) were utilized for this purpose. The original input image is transformed into an image descriptor's feature vector. Each model calculates the encoded feature vector before extracting the bottleneck features. These bottleneck characteristics represent a low-dimensional vector, significantly reducing the model's training time when compared to retraining after fine-tuning.

Third Phase: Utilize machine learning classifier: Finally, a machine learning classifier was utilized to classify the disease. After saving each model's bottleneck characteristics, the created features were fed into five machine-learning classifiers (Random Forest, Decision Tree, SVM, AdaBoost, and Bagging). All skin images are then classified as either other instances or monkeypox.

3 Experimental Procedure and Result

3.1 Dataset description and experiment setup

In this study, the "Monkeypox Image Lesion Dataset " or "MILD" dataset was used, which is collected from kaggle [17], to train all the models. This dataset contains two class: monkeypox patient and non-monkeypox images. The primary focus is on differentiating monkeypox cases from other diseases with almost similar symptoms like chickenpox and measles. Therefore, this dataset is used as it contains skin lesion images of patients with monkeypox, chickenpox, and measles. Some samples from the used dataset are shown in Fig 1

The dataset includes 228 images, 102 of which are monkeypox and 126 are other conditions (chickenpox, measles, etc.). Various data augmentation techniques (rotation, reflection, translation, etc.) were used on the training and validation datasets to improve classification performance. Additionally, three-fold cross-validation was used to minimize bias during training. In the final split, 70% of the data was allocated to training, 20% to validation, and 10% to testing. Google Colab was chosen for the GPU and support for Keras library with TensorFlow backend an.

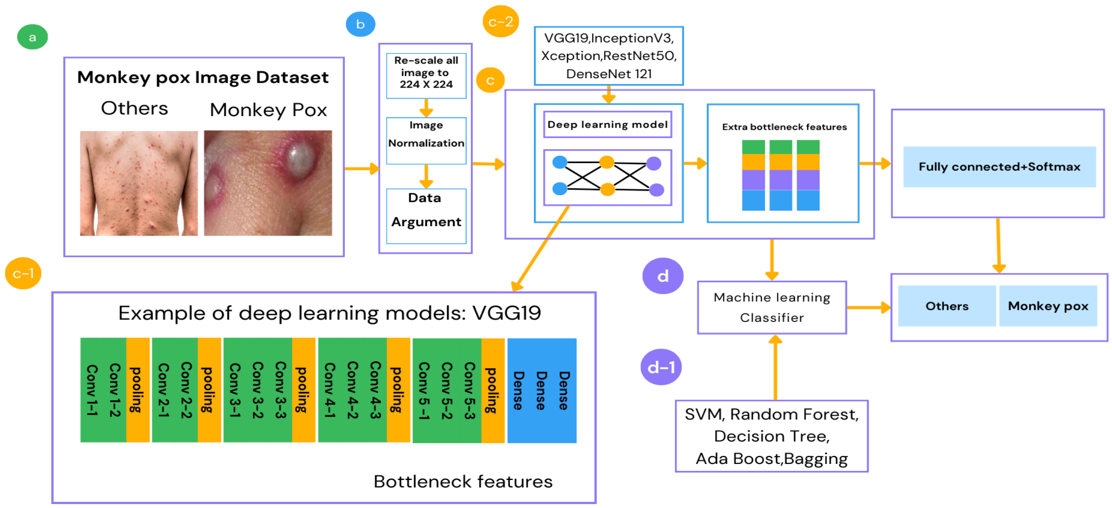

Fig. 2. Workflow of the proposed methodology for monkeypox detection: (a) data collection; (b) data pre-processing includes resizing the raw image to 224x224 size, data augmentation and normalization; (c) features extraction using pre-trained deep learning models and (d) finally classify images using transfer learning and traditional machine learning classifiers.

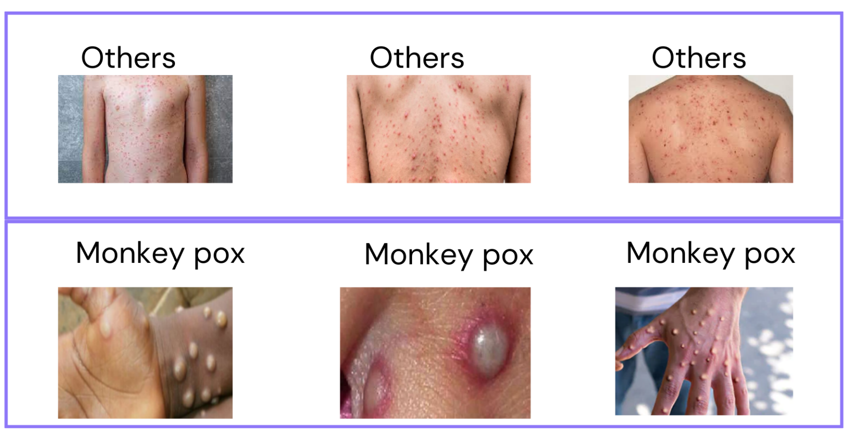

Fig. 3. Some samples from the used data.

3.2 Performance Evaluation Metrics

To evaluate the effectiveness of the proposed method, four essential metrics are used: accuracy, precision, sensitivity (recall), and F-1 scores.

$$Accuracy(Acc.) = \frac{(TP + TN)}{(TN + FP + TP + FN)} \tag{1}$$

$$Sensitivity(Sen.) = \frac{TP}{(TP + FN)} \tag{2}$$

$$Precision(Pre.) = \frac{TP}{(TP + FP)} \tag{3}$$

$$F1 = \frac{2TP}{(2TP + FP + FN)} \tag{4}$$

3.3 Results and Discussion

First, three pre-trained DL models were utilized to separate skin lesion images, and four evaluation indexes are used for evaluation. This transfer learning strategy has demonstrated remarkable outcomes in the used dataset, as shown in Table 1. The ResNet50 showed an outstanding accuracy of 97.68%. The model's influence is highly stable compared to other models' effects, with a standard deviation of just 0.14%. Furthermore, it should be highlighted that the ResNet50 model has strong sensitivity (96.16%), which is crucial since the target was to reduce the percentage of missed diagnoses of monkeypox to the absolute minimum. The model has a precision of 98.35% when classifying typical instances, which is a similarly good performance. The F1 Score is 97.45%, demonstrating that the ResNet50 model is more effective in differentiating between others and monkeypox cases.

In Fig 4, the training and validation loss and the training and validation accuracy of the ResNet50 model were demonstrated. Figure 4 shows that the lowest validation loss was achieved at epoch 25. Training was stopped at this point to avoid over-fitting.

This research combines pre-trained deep learning models with classical ML classifiers to enhance Monkeypox diagnosis accuracy and generalizability. Three pre-trained models were used for feature extraction and combined with five ML classifiers, including SVM, AdaBoost, Random Forest, and Bagging DT (Decision Tree), to differentiate between normal and Monkeypox cases. The assessment findings for various DL models and five ML methods are given in Table 2–Table 4. From the experimental results, Combining deep learning (DL) feature

Table 1. Results for applying the transfer learning approach on five pre-trained models.

Model	Acc.%	Sen.%	Pre.%	F1%
VGG19	95.64	91.73	97.70	93.81
ResNet50	97.68	96.16	98.35	97.45
DenseNet121	91.24	96.05	97.91	94.46

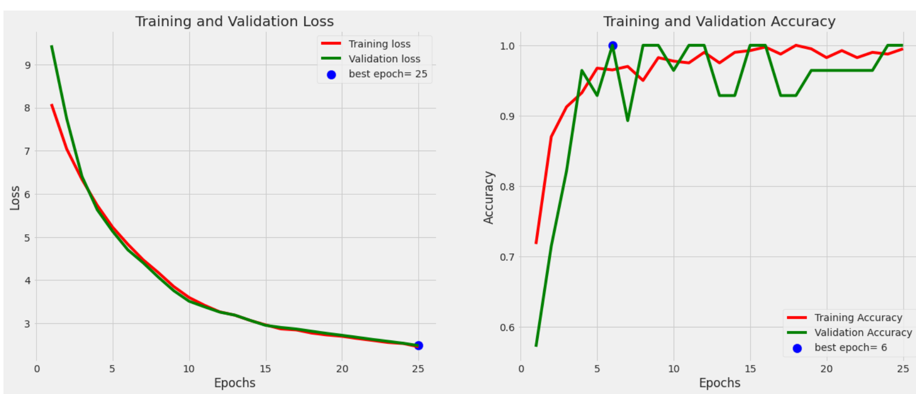

Fig. 4. Loss and Accuracy curve during training and validation for ResNet50 model.

extraction with conventional machine learning (ML) classifiers dramatically outperformed traditional transfer learning for Monkeypox diagnosis. Notably, each pre-trained DL model yielded excellent results when paired with various ML classifiers.

Table 3 has the best performance compared to others, and the accuracy of ResNet50 + SVM reaches 99.98%. Compared with other methods, the precision and F1 score are also optimal (99.81%) The sensitivity is 99.27% which indicates that the proportion of monkeypox is accurately identified. This method achieves an impressive precision of 99.55%, exceeding the ResNet50 transfer learning model by a significant margin (see Table 1). This improvement stems from several factors. First, pre-trained models capture high-level, highly discriminative details, and monkeypox skin lesions are easier to identify than other lesions. This allows classical ML methods like SVM, known for strong learning and generalization, to leverage these features effectively, enhancing performance. Furthermore, the confusion matrix and area under the ROC curve for the ResNet-SVM hybrid model, as shown in Figure 5 and Figure 6, were generated. From these figures, it can be observed that the proposed hybrid model accurately identifies the monkeypox disease from the image with an accuracy of 99.56%. The misclassification rate is 0.0044%, which indicates the effectiveness of the proposed system.

In this research, A comparative analysis of recent research on monkeypox detection using deep learning was conducted, as shown in figure 7. The proposed system outperforms other research works in this domain.

Model	**Acc.%**	**Sen.%**	**Pre.%**	**F1%**
VGG19+SVM	96.98	98.23	94.16	96.63
VGG19+RF	96.98	97.06	96.35	97.06
VGG19+DT	95.30	94.24	95.62	94.24
VGG19+AdaBoost	96.98	96.38	97.08	96.38
VGG19+Bagging	98.32	98.53	97.81	98.53

Table 2. Performances of VGG19 combined with different classifiers

Model	**Acc.%**	**Sen.%**	**Pre.%**	**F1%**
ResNet50+SVM	99.98	99.27	99.55	99.81
ResNet50+RF	98.97	96.35	97.78	99.06
ResNet50+DT	96.28	97.16	97.73	96.91
ResNet50+AdaBoost	97.27	96.43	96.24	94.81
ResNet50+Bagging	96.51	98.64	98.64	98.45

Table 3. Performances of ResNet50 combined with different classifiers

Model	**Acc.%**	**Sen.%**	**Pre.%**	**F1%**
DenseNet121+SVM	96.99	96.05	97.20	97.02
DenseNet121+RF	95.44	91.41	98.10	95.55
DenseNet121+DT	96.04	95.43	97.22	95.63
DenseNet121+AdaBoost	96.04	94.60	96.02	96.52
DenseNet121+Bagging	97.22	94.78	99.02	96.22

Table 4. Performances of DenseNet121 combined with different classifiers

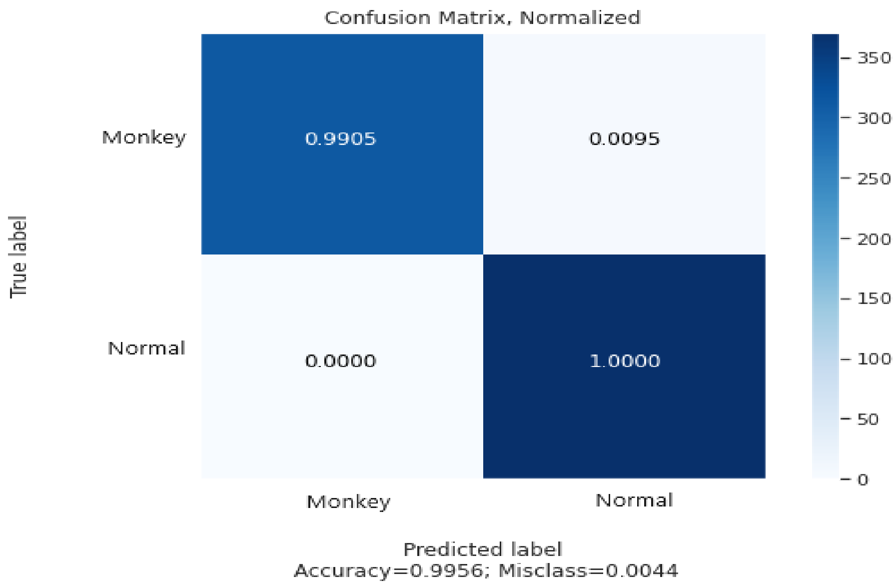

Fig. 5. Confusion matrix of the proposed ResNet-SVM model

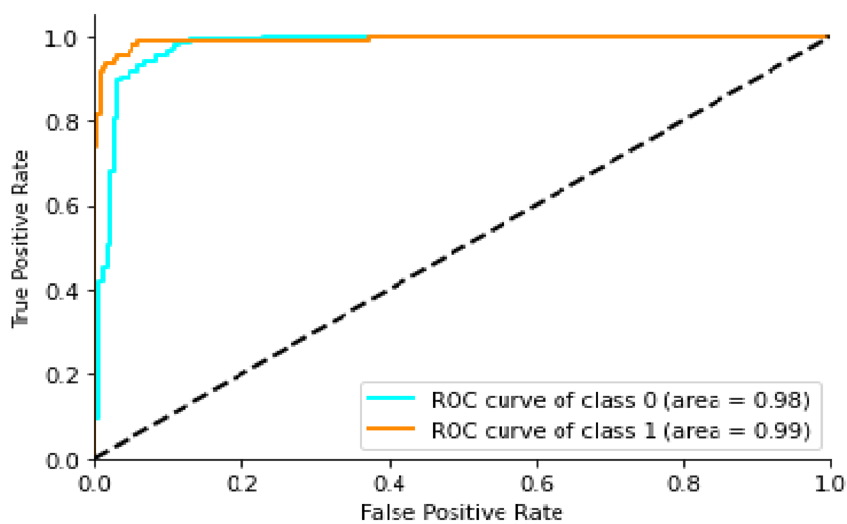

Fig. 6. ROC curve of the proposed ResNet-SVM model

In summary, combining ML with deep feature extraction consumes considerably less time than traditional transfer learning while delivering superior performance. As a result, the fusion of deep features with machine learning techniques surpasses traditional transfer learning approaches in terms of both performance and time efficiency.

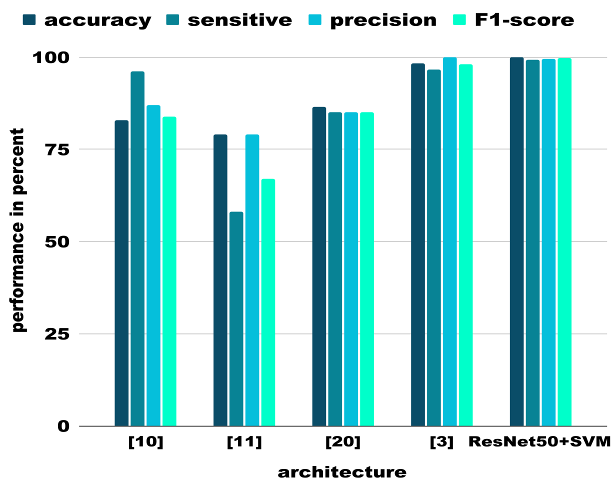

Fig. 7. Performances comparison of the proposed system with some existing works(in %)

4 Conclusion

This study introduced an effective diagnostic technique to distinguish monkeypox patients from others. two main approaches were employed: the traditional transfer learning method and a fusion of a pre-trained deep learning (DL) model with conventional machine learning (ML) classifiers. Notably, the ResNet50 model demonstrated outstanding specificity and sensitivity. However, when compared to other relevant research, traditional transfer learning methods are still inferior compared to other relevant research.The combination of deep feature extraction and ML classification presents a promising diagnostic strategy for identifying monkeypox patients. This research utilized three pre-trained DL models to extract bottleneck features and applied five ML classifiers for identification. The deep feature extraction method proved significantly faster than conventional transfer learning. Furthermore, the integration of deep feature extraction with ML techniques outperforms classic transfer learning approaches in terms of both performance and time efficiency. The rigorous experimental results demonstrate that the system outperforms existing state-of-the-art methods. In the future, the robustness of the architecture will be enhanced by training the system with a larger and more diverse dataset.

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