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DIAGNOSIS OF MONKEYPOX USING INTERPRETABLE DEEP LEARNING

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Abstract: The worldwide spread of monkeypox after the Coronavirus pandemic underlines the need for early distinguishing proof and the board to forestall pandemics. VGG16, ResNet50, MobileNetV2, and VGG19 were further developed utilizing Transfer Learning (TL) approaches in this work. Deep Learning (DL) is a practical and open disease expectation strategy. Modified VGG19 and MobileNetV2 models performed best, accomplishing uncommon precision. These discoveries feature the significance of DL-based early disease distinguishing proof in battling arising wellbeing chances, particularly in far off and asset obliged areas. The task's 100 percent accuracy utilizing Hybrid MobileNetV2model shows a truly solid monkeypox indicative device. Adding a Flask front-end interface makes client testing more straightforward. Client validation gets the Monkeypox indicative help by permitting just approved clients.[62]

***Index terms** - Deep learning, monkeypox, disease diagnosis, transfer learning, image processing.*

1. INTRODUCTION

MPXV disease, frequently known as monkeypox, is brought about by the infection of a similar name and normally influences monkeys [1]. African, Central, West African, and Asian monkeypox are normal [2]. While it might taint any species, the infection communicates to people by gnawing a bat or monkey [3]. Early monkeypox side effects incorporate fever, sluggishness, cerebral pain, and solid touchiness. It seemed to be chickenpox, smallpox, and measles. Before the rash shows up, extended organs behind the ear, underneath the jaw, on the neck, or in the crotch demonstrate it [4,64]. The infection is seldom dangerous, however extreme contaminations can cause sepsis, pneumonia, and visual impairment [5]. Monkeypox only occasionally influences people, yet the minor likelihood of contamination ought to make individuals mull over seeing monkeys and rodents, particularly in regions where flare-ups are more normal. The CDC predicts a huge number of people might get a new monkeypox strain before long [6].

In 2014, monkeypox was rediscovered in the Republic of Congo in West Africa [7], [8]. Monkeypox, but less notable than Ebola or Zika, could turn into an overall medical condition in the event that not halted. The infection has been spreading gradually, and

ISSN2454-9940
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Vol 18, Issue 3, 2024

monkeypox cases are rising regular. As of June 6, 2022, the infection had spread to 29 countries with 1029 affirmed cases, as per CDC [9]. There are no viable monkeypox treatments [10], [11]. Be that as it may, Brincidofovir and Tecovirimat, two oral smallpox meds, are suggested for quick treatment. Inoculation is the most grounded guard against this affliction [12], [13].

Monkeypox, smallpox, and measles side effects are indistinguishable, making determination troublesome without a lab test [14]. The best popular finding is by electronic microscopy of skin injuries. Coronavirus testing frequently utilizes polymerase chain reaction (PCR) [15], [16]. Lab testing commonly utilize PCR. During Coronavirus, the PCR test unit neglected to analyze 40% of patients [17], [18], requiring extra tests to further develop precision. It will be challenging to give sufficient tool compartments to test Monkeypox and Coronavirus patients in the event that the sickness turns into another worldwide scourge. These instruments are excessively costly for the vast majority rich countries to routinely utilize. In the event that Monkeypox [63] or Coronavirus turns into an overall pandemic, getting sufficient testing packs might be risky. The high cost of making these packs makes them unsatisfactory for the majority affluent countries [19].

Machine learning (ML) has shown guarantee in clinical imaging and disease recognition [20], permitting malignant growth, pneumonia, and Coronavirus to be perceived without specialist contribution [21]. This year, a few exploration tracked down that deep learning (DL)- based structures may be a convenient choice for distinguishing Chickenpox and Measles, which have tantamount side effects to Monkeypox [22], [23], [24]. For example, Chae et al. utilized a deep neural network (DNN) and LSTM model to analyze chickenpox better than the autoregressive integrated moving average (ARIMA) model [22]. Arias and Mejía [23] fostered a DL strategy to distinguish the possibly blinding varicella-zoster infection. The infection might be distinguished with 97% accuracy utilizing the model. CNN helped Bhadula et al. [24] find skin issues. A CNN model developed by the creators recognizes skin inflammation and lichen planus with 96% and 92% accuracy [24]. In 2019, Sriwong et al. utilized CNN to determine skin issues to have 79.2% accuracy. Recognizing actinic, basal, and harmless keratoses, among other skin sicknesses, was the creators' principal center [25].

2. LITERATURE SURVEY

Monkeypox is spreading in endemic regions. Monkeypox infection is turning out to be more significant, yet we have hardly any insight into its host range and sylvatic upkeep. We report the repeat of monkeypox infection in a wild western chimpanzee local area in Taï Public Park, Ivory Coast, where people have resided. Monkeypox can cause a serious respiratory condition without an expansive rash, as shown by everyday observation. In 949 harmless examples, we found something like two monkeypox viral heredities and irresistible particles in defecation and flies, recommending backhanded transmission [1]. Our discoveries show that the Taï chimpanzees' eating routine, fundamentally hunting sympatric monkeys, didn't change or move towards rat utilization before the flare-ups, recommending that the unexpected rise of monkeypox infection in this populace is reasonable because of changes in the infection's nature. Throughout recent many years, long haul mortality

ISSN2454-9940
www.ijasem.org
Vol 18, Issue 3, 2024

reconnaissance information from Taï Public Park demonstrates negligible going before infection movement. [61] We infer that extraordinary primate sentinel frameworks that catch longitudinal conduct and wellbeing information can help make sense of zoonotic microorganism the study of disease transmission and clinical show.[64]

In West and focal Africa, a few rat and nonhuman primate species have zoonotic monkeypox infection. Monkeypox was recognized in 1958, however human cases didn't show up until the mid 1970s. Since smallpox was far reaching, diseases were logical camouflaged before this time [2]. Nonetheless, human monkeypox infection diseases and flare-ups including human-to-human transmission have expanded since the 1970s. This ascent might be credited to expanded checking, ecological crumbling, and urbanization of monkeypox viral reservoir(s) and human contamination nidus areas. Monkeypox infection taints a few creature animal groups across huge geographic reaches because of viral hereditary inclinations [1,2,4]. When restricted to Africa, monkeypox infection has spread, in one case intercontinentally, proposing that human monkeypox contaminations might increment. Since monkeypox infection is kept up with in wild creatures, it is less helpless to annihilation. Human immunization is turning out to be less compelling in controlling poxvirus contaminations in an immunocompromised populace, particularly in Sub-Saharan Africa because of HIV. Expanded human monkeypox infection diseases, particularly in immunocompromised individuals, may permit the infection to adjust and make due in people.

A smallpox-like contamination, monkeypox can cause serious clinical issues. There are no customary or optimal monkeypox (MPX) clinical consideration proposals, particularly in low-asset settings [5]. Consequently, patients might have long ailments and awful outcomes. Figuring out clinical indications, including entanglements and sequelae, and illness characteristics that might anticipate seriousness and unfortunate results is fundamental for further developing treatment. Trial and unconstrained monkeypox infection contamination of non-human primates might offer pharmacological intercessions to work on understanding treatment. These exploration have commonly involved MPX as a smallpox sickness copy to battle bioterrorism.

The worldwide work to find and portray irresistible specialists, decipher their sickness pathways, and make protection measures and treatments for the vast majority of the world's most dangerous contaminations has dealt with various endemic ailments for a really long time. Indeed, even while progress has been made, new microbial perils keep on undermining irresistible diseases. Arising and reappearing dangers incorporate HIV/Helps, intestinal sickness, TB, flu, SARS, West Nile infection, Marburg infection, and bioterrorism [6]. Answering these challenges requires another countermeasure improvement approach. U.S. government-supported biomedical analysts have generally centered around major exploration and thought improvement, passing on item advancement to the drug area. Be that as it may, government contribution in centered countermeasure advancement is developing. Government, business, and scholastics should cooperate to save and update our weapons store to

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

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www.ijasem.org

Vol 18, Issue 3, 2024

outfox the microorganisms that undermine humankind until the end of time.

Another pestilence looms as the globe recuperates from Coronavirus. Monkey Pox is another worldwide wellbeing danger. It might turn into a pandemic in the wake of spreading to 40 countries [8]. Monkey Pox looks like chickenpox and measles, making determination testing. Fostering another test pack at this beginning phase is hard for specialists. This exploration offers computerizing diagnostics with deep learning models. This study looks at ResNet50 [33], [34], [35], EfficientNetB3, and EfficientNetB7 execution. This study shows early Monkey Pox Skin Injury recognizable proof. This work shows promising discoveries on a confined dataset, however a greater dataset with more photographs from different countries is required.[66]

3. METHODOLOGY

i) Proposed Work:

Deep learning and transfer learning are utilized to make a more exact Monkeypox determination model. It utilizes many deep learning models including transfer learning.VGG16, ResNet50, MobileNetV2, and VGG19 are used. The task progressed utilizing Hybrid MobileNetV2model, which arrived at 100 percent accuracy and made Monkeypox determination more reliable.[65] Adding a Flask front-end interface makes client testing more straightforward. Client verification gets the Monkeypox indicative help by permitting just approved clients.

ii) System Architecture:

To tweak pre-prepared deep learning model(s), we adjusted the highest layers for characterization while freezing the underlying layers. This study's suggested models' stream graph is displayed in Figure 1. In spite of changes in layer count (typically initial 7), layer activities, and design, these models actually use highlight extraction and various leveled learning. Our model purposes transfer learning models VGG16, InceptionResNetV2, ResNet50, ResNet101, MobileNetV2, and VGG19 [31-37]. Utilizing pre-prepared models on ImageNet does this. The pre-prepared model's head is frozen, and the proposed model's TL engineering utilizes it. Pre-prepared models in TL. Adjusted layer. are successive while working with little datasets since they permit the organization to utilize data from a lot of information. The pre-prepared model's convolutional layers extricate highlights, which are input into a completely associated layer prepared to sort ImageNet objects. This pre-prepared model works on the proposed model's exhibition, particularly with insignificant preparation information.

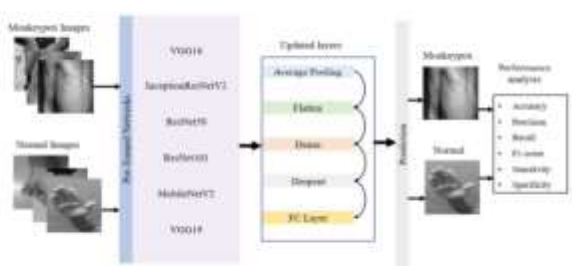

Fig 1 System Architecture

iii) Dataset collection:

The Monkeypox dataset from clinical and research offices is vital for our undertaking. We utilize this enhanced and arranged picture assortment to prepare

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Vol 18, Issue 3, 2024

our deep learning calculations to analyze monkeypox precisely [62].

Fig 2 Dataset images

iv) Image Processing:

Autonomous driving systems use image processing to distinguish objects in different levels. Upgrading the information picture for examination and adjustment starts with mass item transformation. Following this, the calculation's objective classifications are determined by characterizing object classes. Jumping boxes are likewise characterized to demonstrate where things ought to be in the image. Changing over handled information into a NumPy cluster is fundamental for mathematical calculation and examination.[68]

Stacking a pre-prepared model with enormous datasets follows. This includes getting to the pre-prepared model's organization layers, which incorporate learnt highlights and boundaries for compelling item recognizable proof. Extraction of result layers gives last expectations and helps object acknowledgment and arrangement.

Adding the image and explanation record in the image processing pipeline guarantees total information for examination. Switching BGR over completely to RGB changes the variety space, and a cover features significant qualities. A last resize enhances the picture for handling and examination. This total image processing approach lays the foundation for strong and exact item acknowledgment in independent driving frameworks' dynamic setting, further developing street security and navigation.

v) Data Augmentation:

Data augmentation is fundamental for creating different and solid preparation datasets for ML models, particularly in picture handling and PC vision. The first dataset is improved by randomizing, pivoting, and twisting the picture.

Picture changeability is made by randomizing brilliance, difference, and variety immersion. This stochastic strategy works on model speculation to new information and different conditions.

Changing the picture's direction by degrees is called revolution. This increase strategy helps the model to distinguish objects from assorted points, repeating genuine conditions.

Scaling, shearing, and flipping change the image. These mutilations look like true article look and direction, advancing the dataset.

These information increase techniques extend the preparation dataset, assisting the model with gaining hearty highlights and examples. This improves the model's speculation and execution on various and troublesome test conditions. Information expansion lessens overfitting, work on model execution, and further develop AI model constancy, outstandingly in independent driving picture acknowledgment.

vi) Algorithms:

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www.ijasem.org

Vol 18, Issue 3, 2024

VGG16 is a straightforward and successful 16-weight layer CNN. It succeeded in picture acknowledgment. The examination utilizes picture order force to be reckoned with VGG16. Its obvious design can analyze monkeypox from pictures [31].

```
#train existing VGG16 algorithm by modifying its layer to predict monkey pox
#create VGG16 object
vgg16 = VGG16(input_shape=(X_train.shape[1], X_train.shape[2], X_train.shape[3]), include_top=False, weights='imagenet')
for layer in vgg16.layers:
    layer.trainable = False #freeze last layer of VGG16 model
vgg16_model = Sequential()
vgg16_model.add(vgg16)#add vgg16 as base model for further modification
vgg16_model.add(GlobalAveragePooling2D())#adding modifying layers
vgg16_model.add(Dense(512, activation = 'relu'))
vgg16_model.add(Dropout(0.5))
vgg16_model.add(Dense(y_train.shape[1], activation = 'softmax'))
#compile and train the model
vgg16_model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
if os.path.exists("model/vgg16_weights.hdf5") == False:
    model_check_point = ModelCheckpoint(filepath='model/vgg16_weights.hdf5', verbose = 1, save_best_only = True)
    hist = vgg16_model.fit(X_train, y_train, batch_size = 32, epochs = 10, validation_data=(X_test, y_test), callbacks=[model_ch
    f = open('model/vgg16_history.pckl', 'wb')
    pickle.dump(hist.history, f)
    f.close()
else:
    vgg16_model = load_model("model/vgg16_weights.hdf5")
#perfrom prediction on test data
predict = vgg16_model.predict(X_test)
predict = np.argmax(predict, axis=1)
y_test1 = np.argmax(y_test, axis=1)
calculateMetrics("VGG16", predict, y_test1)#call function to calculate accuracy and other metrics
```

Fig 2 VGG16

ResNet50 leftover blocks take care of the disappearing angle issue in this 50-weight layer deep CNN plan. Depth makes ResNet50 great at gathering complex visual qualities. This assists with troublesome exercises like monkeypox conclusion.

```
#create resnet50 object as the base model
resnet = ResNet50(input_shape=(X_train.shape[1], X_train.shape[2], X_train.shape[3]), include_top=False, weights='imagenet')
for layer in resnet.layers:
    layer.trainable = False
#now add new layers to resnet to modify architecture to predict monkeypox disease
resnet_model = Sequential()
resnet_model.add(resnet)
#add average pool layer
resnet_model.add(GlobalAveragePooling2D())
#add dense and drop out layer
resnet_model.add(Dense(512, activation = 'relu'))
resnet_model.add(Dropout(0.5))
resnet_model.add(Dense(y_train.shape[1], activation = 'softmax'))
#compile and load the model
resnet_model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
if os.path.exists("model/resnet_weights.hdf5") == False:
    model_check_point = ModelCheckpoint(filepath='model/resnet_weights.hdf5', verbose = 1, save_best_only = True)
    hist = resnet_model.fit(X_train, y_train, batch_size = 32, epochs = 10, validation_data=(X_test, y_test), callbacks=[model_c
    f = open('model/resnet_history.pckl', 'wb')
    pickle.dump(hist.history, f)
    f.close()
else:
    resnet_model = load_model("model/resnet_weights.hdf5")
#perform prediction on test data
predict = resnet_model.predict(X_test)
predict = np.argmax(predict, axis=1)
y_test1 = np.argmax(y_test, axis=1)
calculateMetrics("ResNet50", predict, y_test1)#call function to calculate accuracy and other metrics
```

Fig 4 ResNet50

VGG19 expands VGG16 with 19 weight layers while keeping its straightforwardness and adequacy. VGG19 is a more profound design choice to VGG16 [31]. It decides whether more layers upgrade Monkeypox diagnosis.

```
#now modify VGG19 architecture with new layers
vgg19 = VGG19(input_shape=(X_train.shape[1], X_train.shape[2], X_train.shape[3]), include_top=False, weights='imagenet')
for layer in vgg19.layers:
    layer.trainable = False
vgg19_model = Sequential()
vgg19_model.add(vgg19)
#add average pool layer to vgg19
vgg19_model.add(GlobalAveragePooling2D())
#add dense and drop out layer
vgg19_model.add(Dense(512, activation = 'relu'))
vgg19_model.add(Dropout(0.5))
vgg19_model.add(Dense(y_train.shape[1], activation = 'softmax'))
#compile and train the model
vgg19_model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
if os.path.exists("model/vgg19_weights.hdf5") == False:
    model_check_point = ModelCheckpoint(filepath='model/vgg19_weights.hdf5', verbose = 1, save_best_only = True)
    hist = vgg19_model.fit(X_train, y_train, batch_size = 32, epochs = 10, validation_data=(X_test, y_test), callbacks=[model_ch
    f = open('model/vgg19_history.pckl', 'wb')
    pickle.dump(hist.history, f)
    f.close()
else:
    vgg19_model = load_model("model/vgg19_weights.hdf5")
#perform prediction on test data
predict = vgg19_model.predict(X_test)
predict = np.argmax(predict, axis=1)
y_test1 = np.argmax(y_test, axis=1)
calculateMetrics("Modified VGG19", predict, y_test1)#call function to calculate accuracy and other metrics
```

Fig 5 VGG19

MobileNetV2 lightweight CNN design for versatile and installed applications. Minimal and proficient. [37] Undertaking assesses MobileNetV2's monkeypox diagnosing proficiency. Its unassuming model size speeds surmising in asset obliged settings.

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Vol 18, Issue 3, 2024

Fig 6 Mobilenetv2

A **specialized MobileNetV2** variant upgraded for include extraction. Upgraded highlights speed expectations, saving time for constant applications like clinical diagnostics [37].

Fig 7 Hybrid

4. EXPERIMENTAL RESULTS

Precision: Precision quantifies the percentage of certain events or tests that are well characterized. To attain accuracy, use the formula:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

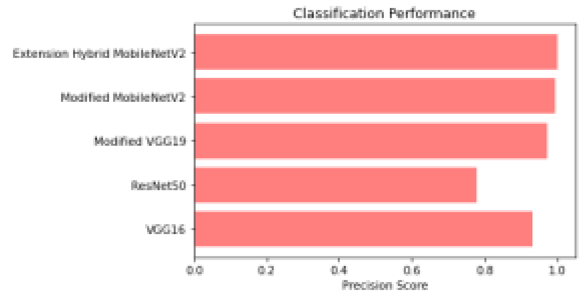

Fig 8 Precision comparison graph

Recall: ML recall measures a model's ability to catch all class occurrences. The model's ability to recognize a certain type of event is measured by the percentage of precisely anticipated positive prospects that turn into real earnings.

$$Recall = \frac{TP}{TP + FN}$$

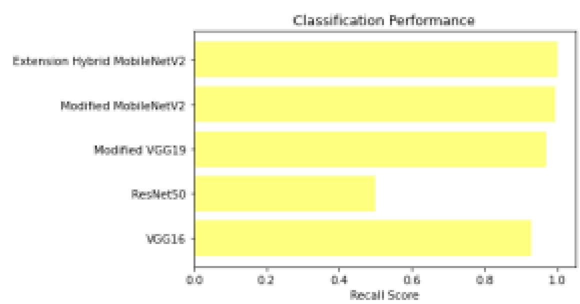

Fig 9 Recall comparison graph

Accuracy: The model's accuracy is the percentage of true predictions at a grouping position.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

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www.ijasem.org

Vol 18, Issue 3, 2024

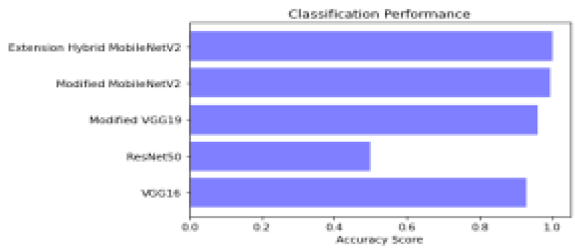

Fig 10 Accuracy graph

F1 Score: The F1 score captures both false positives and false negatives, making it a harmonized precision and validation technique for unbalanced data sets.

$$\text{F1 Score} = 2 * \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} * 100$$

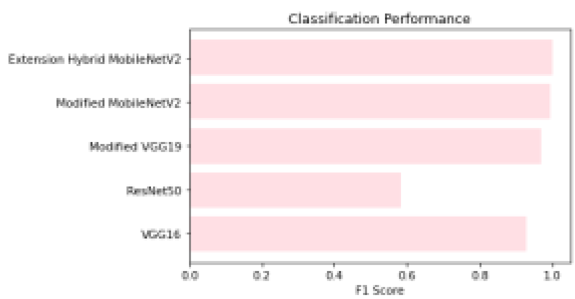

Fig 11 F1Score

ML Model	Accuracy	Precision	Recall	F1_Score
VGG16	93.0	93.053740	93.019502	92.999300
ResNet50	50.0	49.162857	49.624962	41.561477
Modified VGG19	97.0	97.092732	96.979696	96.997296
Modified MobileNetV2	99.5	99.50000	99.504950	99.499987
Extension Hybrid MobileNetV2	100.0	100.0000	100.000	100.0000

Fig 12 Performance Evaluation table

Fig 13 Home page

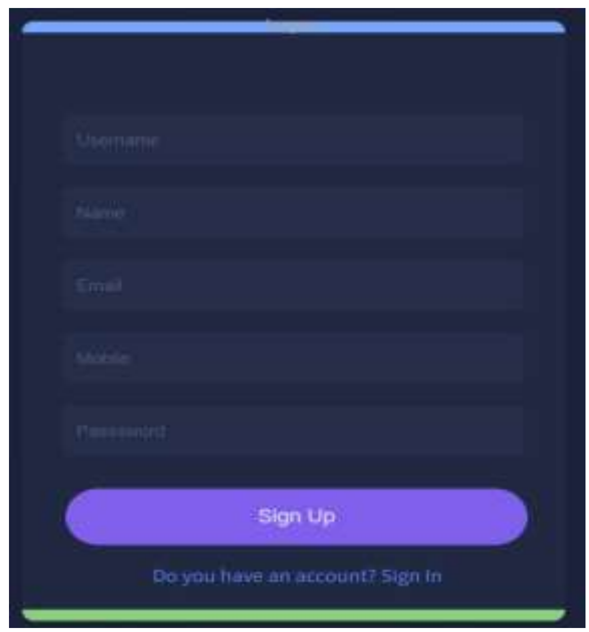

Fig 14 Registration page

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www.ijasem.org

Vol 18, Issue 3, 2024

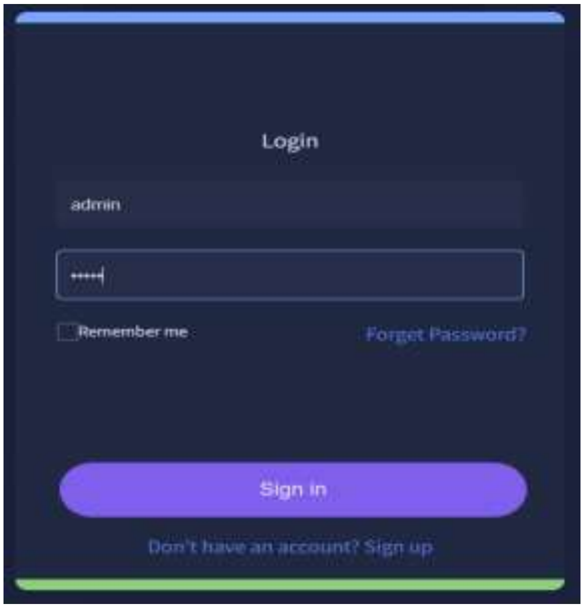

Fig 15 Login page

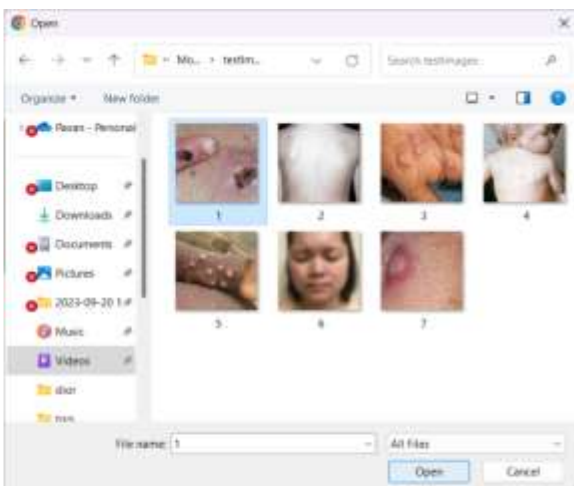

Fig 16 Input image folder

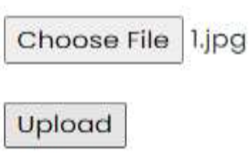

Fig 17 Upload input image

Fig 18 Predict result for given input

5. CONCLUSION

The venture tried deep learning models such VGG16, ResNet50, MobileNetV2, and VGG19 [31], [32], [33], [34], [35], [36], [37] and found that transfer learning can improve monkeypox ailment location. A robotized monkeypox conclusion technique tends to the requirement for quick and exact early recognizable proof, particularly in regions with restricted medical services access, possibly working on quiet results. The incorporated Hybrid MobileNetV2 calculation [37] sets another benchmark for monkeypox analysis with exact and dependable discoveries that will change medical care. Involving Flask for the front-end, we tried the augmentation procedure and information unequivocally. This execution shows the calculation's strong presentation and ease of use in certifiable circumstances, reinforcing its true capacity for more extensive medical services use. This drive advances medical services access, particularly in oppressed regions, by offering an available and precise symptomatic device and exhibiting the advantages of deep learning in ailment conclusion and patient consideration.[70]

6. FUTURE SCOPE

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www.ijasem.org
Vol 18, Issue 3, 2024

The paper shows how transfer learning models and reasonable artificial intelligence might be utilized to build protected and solid monkeypox ailment location calculations. Move learning methods are versatile and important in disease determination, opening huge possibilities for extra review and improvement. This study can make ready for future sickness counteraction and control research, particularly in far off and asset unfortunate spots. Before long, it will be intriguing to perceive how the suggested model deals with a multiclass and gigantic dataset to improve monkeypox finding. Transfer learning and explainable AI in ailment analysis models can further develop medical services symptomatic apparatuses. This study's discoveries and nitty gritty evaluations could assist future analysts and specialists with exploring move learning models and explainable AI for monkeypox ailment recognition.

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