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Mobile Application for Skin Disease Classification Using CNN with User Privacy

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Abstract: The human body faces numerous challenges, and the skin, in particular, proves to be difficult to analyze mechanically because of its unevenness, complexion, presence of hair, and other alleviated attachments. Consequently, there is a growing need for an accurate, automatic system for detecting skin diseases. Due to dataset imbalance and data security issues, classifying skin diseases using medical images is difficult. The primary reason for the lack of accessible datasets is privacy and confidentiality concerns related to medical data sharing. In Medical Image Analysis (MIA), the Convolution Neural Network (CNN) performance for classification and a federated learning strategy for data privacy protection is impressive. Our results show that CNN can achieve an accuracy score of 0.90. We suggest a mobile application for classifying skin diseases using CNN and a federated learning strategy. The analysis of human skin with this mobile app is outstanding while maintaining data security.

Keywords: Dataset imbalance; Medical Image Analysis; Convolution Neural Network; Federated learning; Data security.

1. Introduction

Prevention of the onset and spread of skin diseases requires early diagnosis. Skin conditions take longer to diagnose and cure, and they are more expensive for the sufferer, both physically and financially. The type and severity of a skin ailment are frequently unknown to most people. Some skin conditions take several months to show symptoms, which gives the infection time to develop and spread. Therefore, we advise applying image processing to analyze the skin conditions. By capturing a digital image of the damaged skin area, this technology analyses the image to identify the illness kind.

- Medical Image Analysis: The study of using different types of images and digital image analysis tools to solve or analyze medical problems is known as medical image analysis (MIA). To identify illnesses and arrange for immediate medical treatments like surgery or research, medical image processing comprises evaluating and looking at 3D images of the human body that are often gathered through a CT or MRI scanner. Medical image processing is a task by radiologists, engineers, and physicians to comprehend the anatomy of specific individuals or populations. The volume of the reconstructed image is frequently manipulated for medical users to split and modify different anatomically intriguing regions, such as bone and tissue. The algorithms can control sicknesses and health hazards while fostering good health [1].
- Computer-aided diagnosis: Systems that help healthcare professionals understand medical images are computer-aided detection (CADe), also known as computer-aided diagnosis (CADx). Radiologists and other medical professionals must swiftly and thoroughly analyze and assess the vast data from imaging

procedures such as X-rays, MRIs, endoscopes, and ultrasound diagnostics. CAD systems analyze digital photos or videos for distinctive looks and highlight noticeable areas, such as potential ailments, to provide information to help a professional's choice [2].

- Federated Learning: Federated Learning enables the execution of machine learning tasks without storing training data on the cloud [11-15]. Instead, it allows mobile devices to collaborate in developing a collective prediction model while keeping all training data locally on the device. The concept of extending model training to the device goes beyond using local models solely for making predictions on mobile devices. [3].

Federated Learning provides a way to maintain privacy while still benefiting from improved models, reduced latency, and lower power consumption. Moreover, this approach offers an immediate benefit: apart from updating the shared model, it allows for immediate utilization of the enhanced model on your device, enabling tailored experiences based on your device's usage [3].

2. Literature Review

The computer-aided diagnosis system, which can validate physicians' decisions, is becoming a more crucial instrument in clinical treatment. This study devised a new technique for detecting unnatural brains in magnetic resonance imaging. First, our brain images were used to train a pre-trained AlexNet with batch normalization layer modifications. The remaining few layers were then replaced with an advanced learning machine. A search approach was recommended to find the appropriate number of layers that should be replaced. Finally, a chaotic bat method improved the performance of the cutting-edge learning machine's categorization function. The outcomes of the five hold-out validation studies demonstrated that our technique provided cutting-edge performance [4].

Develop the best ResNet model for categorizing photos of healthy skin and melanoma malignancy. ISIC 2018 was the dataset that was utilized. Because ResNet won the 2015 ILSVRC competition, it is used. ResNet 50, 40, 25, 10, and 7 are ResNet architecture models. The architecture is trained using enhanced and under sampling data. Using the F1 Score, the validation outcome for each model was determined [5].

After validation and the model's F1 Score result, the results were compared against each other to determine which model was the best. For ResNet 50 without augmentation, the best design has a validation accuracy of 0.83 and an F1 score of 0.46 was achieved.

A skin cancer detection app based on Android is utilized in this work to apply the Faster R-CNN and MobileNet v2 algorithms. Both proposed architectures were taught to recognize Actinic keratosis and melanoma skin cancer targets through pictures. Without considering factors like gender, age, or other characteristics, the 600 photographs in the collection were divided into actinic keratosis and melanoma images. An Android software was developed for this study that uses smartphones' camera to identify skin cancer. An intelligent screening system was utilized, which consisted of the Faster R-CNN and MobileNet v2 models. This investigation used two testing techniques—the Android camera and the Jupyter Notebook. According to the experiment's findings, MobileNet v2 and Faster R-CNN achieved good accuracy when tested using Jupyter and a smartphone [6].

This study presents the most recent analysis of deep learning applications in processing medical images related to COVID-19. After that, we briefly introduce deep learning and the most current advancements in its application to healthcare. The following three use examples demonstrate that Deep-learning applications are being used for medical image processing related to COVID-19 in China, Korea, and Canada. Lastly, various challenges and issues related to applying deep learning in medical image processing for COVID-19 are examined. These are anticipated to motivate additional research into containing the crisis and the outbreak, leading to intelligent, healthy cities [7].

This paper provides a helpful suggestion for improving dermoscopic pictures by removing hair and other artifacts utilizing the entire variation in painting technique and sneaky morphological processing. To show the value of improving dermoscopic pictures, a method is also suggested that may produce skin lesion classification outcomes equivalent to deep neural networks at a cost as low as in Conv 2D. Using this technique, images are subjected to two-dimensional convolution. This approach fully accommodates the information by using three convolution streams. Using a public dataset of 2000 photos of skin lesions, the suggested model is assessed. By using the suggested method to remove hair and artefacts, the classification accuracy of three different types of skin cancer, including nevus, melanoma, and seborrheic keratosis, is increased [8].

Skin-related conditions are among the most widespread around the globe yet their analysis and identification are challenging and require deep subject-matter knowledge. In this study, we offer a technique for diagnosing different illnesses. A dual-stage method that combines computer vision and machine learning is utilized on histopathological characteristics that have been evaluated clinically to efficiently diagnose the illness. Several preprocessing steps are first applied to the skin disease image before feature extraction. According to the histological characteristics that have been identified via the examination of the skin, the second one stage includes the identity of ailments thru the usage of machine studying algorithms. After present process training and trying out for the six sicknesses, the gadget turned into capable of acquire accuracy scores that had been as excessive as 95% [9].

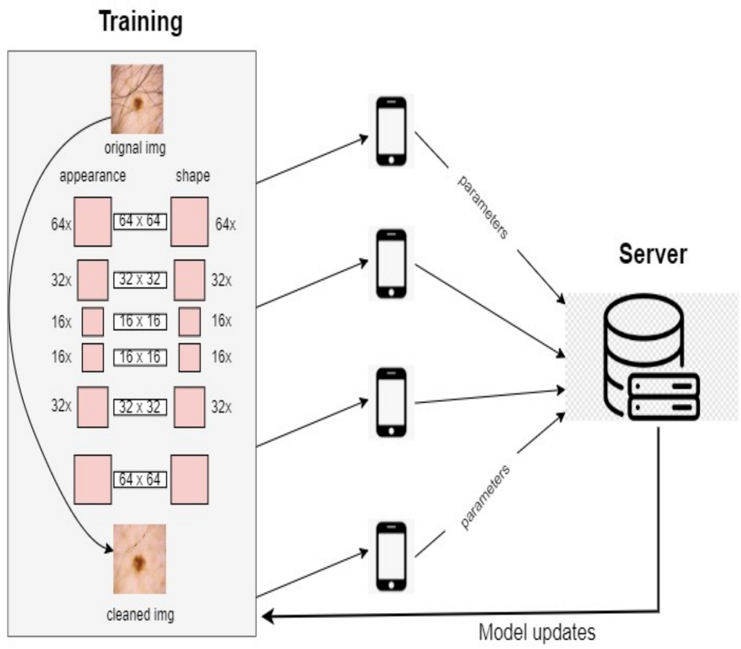

Figure 1. Working of Federated Learning

3. Dataset

The Ham10000 and ImageNet systems had been applied throughout the manner of data collection for the category of skin problems. There are 10,000 dermoscopic images of several skin lesions which can be blanketed inside the Ham10000 series. These lesions encompass melanoma, nevi, and seborrheic keratosis, among others. ImageNet, however, is constituted of an extensive photo series that has more than 14 million images. An "others" magnificence changed into introduced to the ImageNet dataset at some point of the training procedure of the version. This magnificence became used for pics that did now not match the kinds that had been furnished, which enabled a more comprehensive and correct categorization technique. Combining these two datasets provides many images for building and testing skin disease classification models. The availability of these databases will make it easier to develop precise and useful categorization models for skin diseases, ultimately improving patient outcomes.

The Links of Both ImageNet and Ham1000 are given below.

https://www.kaggle.com/hate-speech-and-offensive-language-dataset

https://www.kaggle.com/datasets/akash2sharma/ tiny-ImageNet

In Figure 2 the graph shows the number of images in our dataset. Our dataset is biased toward Melanocytic nevi since it has the most images.

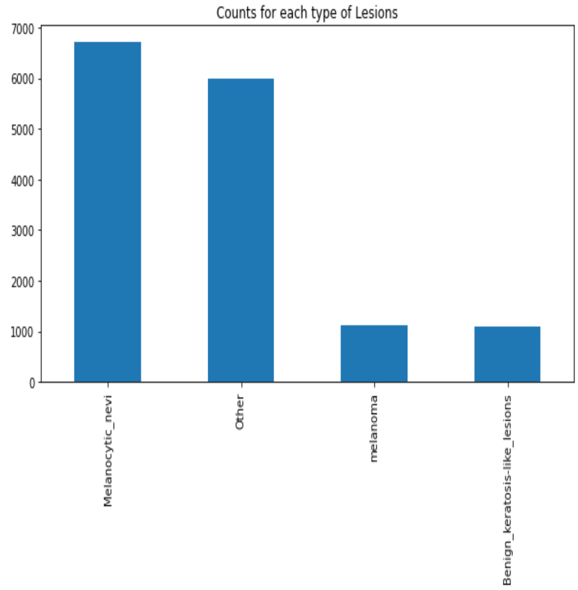

Figure 2. The count of images in each category within our dataset.

In Figure 3 there are some sample images from each class of our dataset.

Figure 3. Dataset sample for skin cancer prediction using CNN of different species.

4. Model Architecture

A Convolutional Neural Network (CNN) model was created for categorizing skin diseases. The CNN architecture included several convolutional layers and max-pooling layers for feature down sampling and dimension reduction. After flattening the output from the convolutional layers, the image was classified into different disease categories using a fully connected layer. This added non-linearity to the model and improved its capacity to recognize complex correlations in the data.

We have made a sequential CNN model with different layers, which are discussed below.

Our CNN model follows the following architectural design.

- First Convolution Layer: This initial layer extracts the different features from the 64x64 input images. With a size of 3 and applying a ReLU activation function., the filter is slid over the image in this layer to execute the mathematical convolution process between the input image and a size 16.
- MaxPooling Layer: The next layer uses a 2x2 window for max pooling after convolution.
- Second Convolution Layer: The convolution layer that follows is the second one, it has 64 size 3 filters and applies a ReLU activation function. The filter is slid over the input image in this layer.
- MaxPooling Layer: The next layer uses a 2x2 window for max-pooling after convolution.
- Third Convolution Layer: The third is the convolution layer, it has 128 size 3 filters and applies a ReLU activation function. The filter is slid over the input image in this layer.
- MaxPooling Layer: The next layer uses a 2x2 window for max pooling after convolution.

- Flatten Layer: A Flatten layer also converts the feature map to a one-dim tensor.
- Dense layer: The eighth layer is fully connected, has 512 hidden units, and activates ReLU.
- Dropout layer: The Dropout layer at position nine has a dropout rate of 0.7.
- Dense layer: The output layer with sigmoid activation is the tenth layer.

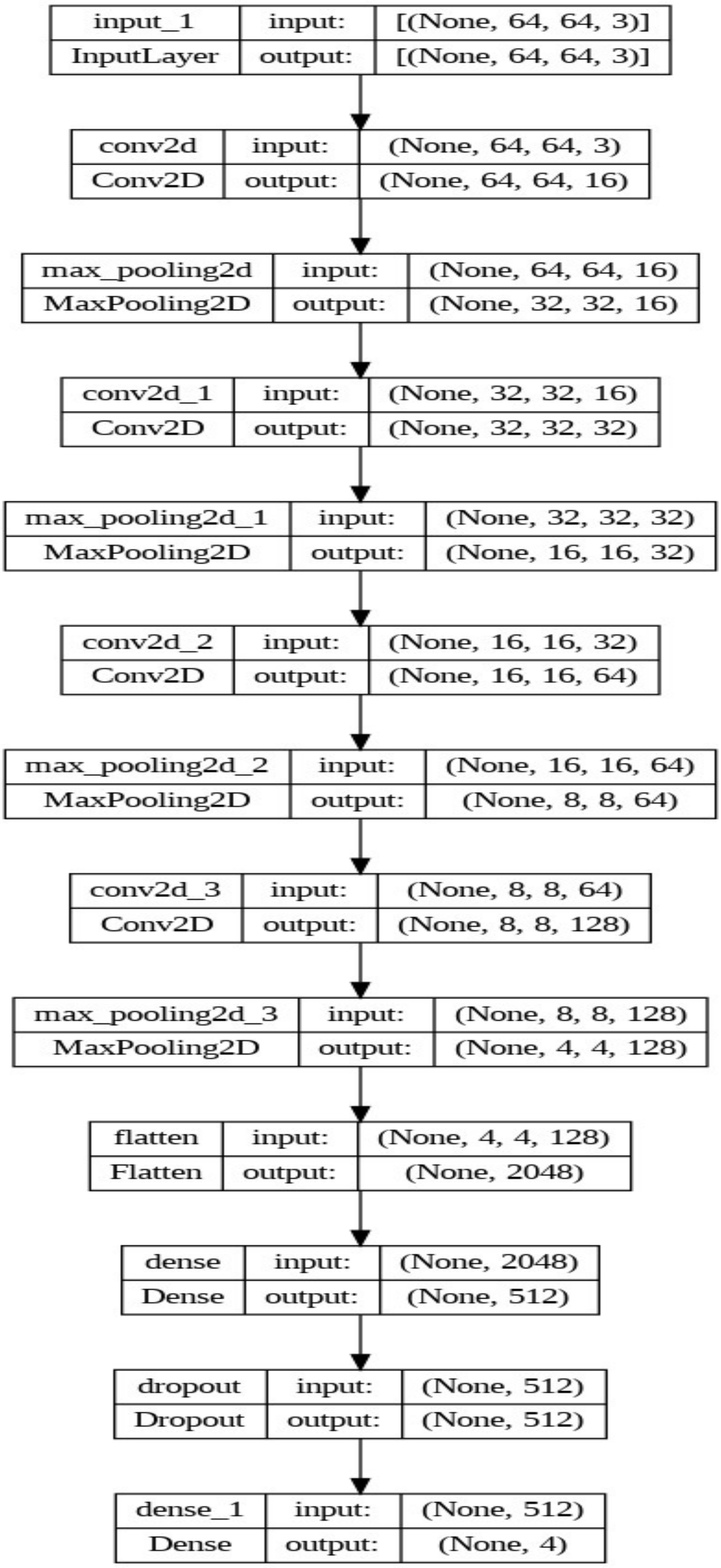

Figure 4. Model

5. Implementation

5.1. Pre-processing

After gathering the experimental datasets, the next step was to combine both datasets into one. Our data frame has all the IDs of images and their corresponding disease names. After the merging, we performed the following tasks on the dataset.

- Add the path column in the data frame in which the paths of all images were added.
- Remove the rows with NaN values
- Add images in the form of a tensor array in a column
- Resize the images to 64x64 to train the model

5.2. Training

After this preprocessing, we used Random Over-Sampler to augment the dimensions of our dataset to ensure that it is balanced. Now, we possess a total of 24,138 images. From this, we did an 80-20 split for training and testing, respectively. Nineteen thousand three hundred ten records were used for training and 4828 for testing.

Our model was trained using the Adam optimizer with a learning rate 0.0001 and a batch size 16. Early stopping was implemented to halt the training if the validation loss improved for 10 epochs. Our model trained for 68 epochs and then stopped. We achieved an accuracy of 90% on our testing data.

5.3. Implementation on Mobile App

After training to get real-time results, the model will be integrated with a mobile application. We have used react native for building the mobile application. The mobile application can get an image from the gallery or the camera. To integrate the model, First of all, we will have to convert this model to a mobile-friendly format, which is tf lite. TensorFlow provides a tool called TensorFlow Lite converter to convert models to TensorFlow Lite format i.e. .tflite. To add this model to the app, we will have to install the TensorFlow Lite library to our React native app by using npm. The library provides different types of APIs that we can use to load and run .tflite files. Once we have added the library, we will load our model and predict the results. After getting the predicted results, the final output with the symptoms and precautions will be displayed on screen.

6. Results & Discussion

The findings in this section are derived from evaluating our skin disease dataset's test set. We run different pre-trained CNN models to check their accuracy. With DenseNet, we got 0.9014 accuracy; Xception had 0.8693 accuracy; from VGG16, we achieved an accuracy of 0.8954; and from ResNet, we got 0.8501.

Figure 5 illustrates the graphs depicting the accuracy during the training and validation stages for our proposed model compared to the training and validation accuracy graphs of AlexNet and DenseNet. This graph shows how well the model picks up new information from the training data and how well it can generalize to new validation data.

The accuracy of the models is represented on the y-axis of the graphs, while the number of epochs is depicted on the x-axis. In both the training and validation phases, each point on the graphs reflects the accuracy attained by the model at a specific epoch.

Figure 5. CNN Models Training and Validation Accuracy Graph.

Figure 6 shows the training and validation accuracy graphs of our proposed model in comparison with the training and validation accuracy graphs of AlexNet and DenseNet. This graph aids in tracking the model's effectiveness and generalization throughout training.

The loss values of the models are represented on the y-axis of the graphs, while the number of epochs is depicted on the x-axis. For both the training and validation datasets, each point on the graphs reflects the loss value that the model was able to attain at a specific epoch.

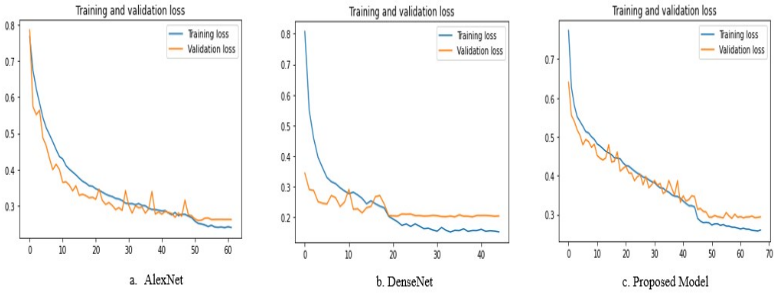

Figure 6. CNN Models Training and Validation Loss Graph.

7. Viscreens for Mobile Applications

The mobile app will function as a one-click procedure in which the user chooses a picture from the mobile gallery or snaps a photo using the mobile camera, with the model predicting the outcomes.

Figure 7 Screen 1 shows the screen on which the user can either select an image of the infected skin area from the gallery or click the image using the mobile camera.

Screen 2 shows the screen on which, after selecting the image, the user will have to click on the get results button to get the desired output.

Screen 3 shows the screen on which the desired output with risk percentage will be displayed after getting a prediction from this phase along with the symptoms and precautionary measures that the user should take to minimize the risk of the specific disease.

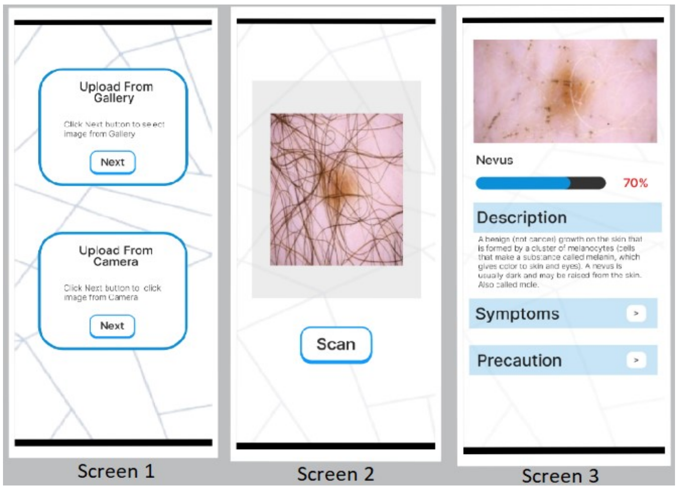

Figure 7. First Screen

8 .Future Goals

The future business goal for our mobile app for skin disease classification is to become the go-to solution for dermatologists and healthcare professionals in accurately diagnosing skin diseases. This goal could be achieved by continually improving the machine learning model to increase accuracy and expanding its features to include more comprehensive information on various skin diseases.

This goal could be achieved using federated learning and building partnerships with dermatology clinics and hospitals, offering them discounted rates and personalized app support. Additionally, marketing campaigns targeting dermatologists and healthcare professionals could be launched to increase awareness and adoption of the app within the medical community.

Overall, becoming the leading solution for skin disease classification in the medical field would not only benefit the success of your app but also have a positive impact on improving the accuracy and speed of skin disease diagnoses, ultimately benefiting patients' health outcomes.

9. Conclusion

In conclusion, developing a mobile app for skin disease classification using Convolutional Neural Networks (CNN) and Federated Learning shows excellent potential for improving the accuracy and efficiency of skin disease diagnoses. By leveraging CNN's ability to recognize patterns and features in images and Federated Learning's ability to train machine learning models without centralized data storage, the app provides a secure and efficient solution [16, 17] for skin disease classification.

References

1. DermNet NZ. (n.d.). Atlas of skin diseases. Retrieved from https://dermnetnz.org/
2. "IBM," [Online]. Available: https://www.ibm.com/topics/smart-contracts#:~:text=Next%20Steps,Smart%20contracts%20defined,intermediary’s%20involvement%20or%20time%20loss.
3. "CoinDCXblog," [Online]. Available: https://coindcx.com/blog/crypto-basics/what-is-a-smart-contract/.
4. "imaginovation Insider," [Online]. Available: https://imaginovation.net/blog/smart-contracts-in-blockchain/.
5. "B.LOG," [Online]. Available: https://blaize.tech/article-type/9-most-common-smart-contract-vulnerabilities-found-by-blaize/.
6. "Etherenum Foundation blog," [Online]. Available: https://blog.ethereum.org/2016/06/17/critical-update-re-dao-vulnerability.
7. "parity," [Online]. Available: https://www.parity.io/blog/security-alert-issued-in-parity-ethereum-wallet-2/.
8. "PubMed Central," [Online]. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7516633/.
9. "Leeway Hertz," [Online]. Available: https://www.leewayhertz.com/best-practices-for-ethereum-smart-contract/.
10. Matteo Maffei, and Clara Schneidewind, "Semantic Framework," [Online]. Available: https://publik.tuwien.ac.at/files/publik_270458.pdf.
11. Ahmed, F., Asif, M. and Saleem, M., 2023. Identification and Prediction of Brain Tumor Using VGG-16 Empowered with Explainable Artificial Intelligence. International Journal of Computational and Innovative Sciences, 2(2), pp.24-33.
12. Saleem, M., Khan, M.S., Issa, G.F., Khadim, A., Asif, M., Akram, A.S. and Nair, H.K., 2023, March. Smart Spaces: Occupancy Detection using Adaptive Back-Propagation Neural Network. In 2023 International Conference on Business Analytics for Technology and Security (ICBATS) (pp. 1-6). IEEE.
13. Athar, A., Asif, R.N., Saleem, M., Munir, S., Al Nasar, M.R. and Momani, A.M., 2023, March. Improving Pneumonia Detection in chest X-rays using Transfer Learning Approach (AlexNet) and Adversarial Training. In 2023 International Conference on Business Analytics for Technology and Security (ICBATS) (pp. 1-7). IEEE.
14. Abualkishik, A., Saleem, M., Farooq, U., Asif, M., Hassan, M. and Malik, J.A., 2023, March. Genetic Algorithm Based Adaptive FSO Communication Link. In 2023 International Conference on Business Analytics for Technology and Security (ICBATS) (pp. 1-4). IEEE.
15. Sajjad, G., Khan, M.B.S., Ghazal, T.M., Saleem, M., Khan, M.F. and Wannous, M., 2023, March. An Early Diagnosis of Brain Tumor Using Fused Transfer Learning. In 2023 International Conference on Business Analytics for Technology and Security (ICBATS) (pp. 1-5). IEEE.
16. Malik, R., Raza, H. and Saleem, M., 2022. Towards A Blockchain Enabled Integrated Library Managment System Using Hyperledger Fabric: Using Hyperledger Fabric. International Journal of Computational and Innovative Sciences, 1(3), pp.17-24.
17. Malik, J.A. and Saleem, M., 2022. Blockchain and Cyber-Physical System for Security Engineering in the Smart Industry. In Security Engineering for Embedded and Cyber-Physical Systems (pp. 51-70). CRC press.