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An Autonomous System for Knee Osteoarthritis Disease Diagnosis using Machine Learning and Standalone Controller

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Abstract:
Due to the recent pandemic, health-related awareness has increased among civilians. Not only this, but from advancements in mobile devices, Health-related mobile applications for disease diagnosis boomed in recent years. The majority of applications diagnose simple decease like colds, fever, headaches, etc., and schedule online doctor's appointments. However, there has been very limited or no support for severe decease like cancer and orthopedic diagnosis. This paper proposes an autonomous disease diagnosis system for knee OA (osteoarthritis) using machine learning methods. The methods for predicting the severity of knee OA are ResNetv2 (Residual Networks 2) and VGG-19 (Visual Geometry Group-19) models are available with prediction accuracy of 64% and 41%, respectively, which is very poor for medical applications. Therefore new method has been proposed using Enhanced VGG-19, which is used to predict the severity of disease and has improved prediction accuracy by up to 97%. After optimizing the stand-alone model, a system is developed where the user has to send a mail or upload an X-Ray image of a particular body part to a specific email ID. The server/system will automatically diagnose for selected disease and generates a report based on that. The server has various optimized trained models for different decease, which will reduce human factors for stakeholders. By using these reports, doctors can save time and the doctor can utilize their time for consulting more patients.
Keywords: ResNetv2, VGG, VGG-19, Knee Osteoarthritis (OA), Machine Learning

1. Introduction

In 2020, the COVID-19 outbreak substantially influenced the mobile health application market. The market would expand by 65.7 percent in 2020, which is significantly higher than in pre-pandemic years. According to an article released by Sensor Tower Incorporation, the total downloads of Health & Fitness applications have been increased by 46% in Europe in 2020 with 829.5 million downloads. This is primarily due to government-backed COVID-19 contact tracing apps, such as India's "Arogya Setu" App and Germany's "Corona-Warn-App" which are both categorized under Fitness and health apps [1] [2].

In addition to this, the smartphone market in India has grown dramatically in recent years, owing to lower internet plans that have increased data usage and developed a diverse mobile app culture. In 2020, 810 million smartphones were sold, and by 2026, that number is predicted to exceed 1.2 billion. Internet penetration has increased dramatically. The healthcare market has also improved due to the use of healthcare applications. The healthcare apps market in India has been driven by an increased focus on patient centred treatment, the emergence of new technology, and changing business models. Applications for wellness monitoring and appointment scheduling have become extremely popular. The demand for chronic disease management apps is likely to skyrocket in the coming years [3] [4].

Small and medium-sized start-ups striving to increase their reach dominate the healthcare application industry. Healthcare stakeholders in India are focusing on employing healthcare applications to compensate for the deficiencies of traditional infrastructure. The usage of mobile health apps for online appointments, lab test reservations, and health monitoring of patients are increased throughout the epidemic [5].

Due to a lack of information, security concerns, and poor application (apps) performance, the market has encountered considerable obstacles. Furthermore, consumers' most significant concerns are fitness and well being management. They have no idea what kinds of healthcare apps are accessible for specific health problems. Even though digitization has altered the Indian healthcare environment, many people are still ignorant of the benefits of healthcare apps. In addition to these, due to the lack of clinical performance data, stakeholders are unsure about the productivity and effectiveness of apps.

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Mobile applications are still lacking in clinical and laboratory performance data. Also, acute diseases like knee OA, various kinds of cancers, COVID-19 detection, etc., current applications are using machine learning and deep learning based approaches particularly in the area of medical science. This paper proposes a system which is capable of predicting multiple disease and generating reports through mobile or email communication. The focus of these study is machine learning based diagnosis and prediction of Knee OA and to develop an email API which can communicate with the stand alone server, passes images, and to generate automated report from the diagnosis at server end. In the proposed system, the server is running on stand along hardware which is NVIDIA Jetson-Nano board.

The rest of the paper is organized as follows: Section 2, descries the detailed Literature review based on existing work. The Proposed system with software architecture is given in section 3. Implementation is presented in section 4 whereas results are discussed and presented in section 5. Finally concluding remarks are presented in section 6.

2. Literature Review

Recent research in knee osteoarthritis, Pingjun Chen has done significant work. Chen's study used a modified YOLOv2 (You Only Look Once2) model for knee joint recognition and a fine-tune CNN (Convolutional Neural Network) model with an unique ordinal loss for knee KL grading [6]. Author have developed cutting-edge knee joint detection and KL grading. The one-stage detector YOLOv2 is ideally suited to detect jobs with less varied object size as well as based on its performance requirement of knee joint detection. On the knee KL grading test, the suggested ordinal loss improves classification accuracy and reduces the MAE between prediction. The performance promise in ordinal classification task, when it is compared using cross-entropy among all popular CNN classification models. The fine-tuned VGG-19 model outperforms as compared to ResNet or DenseNet (Densely Connected Convolutional Networks) modless in classification, validating the performance of CNN models that are highly reliant on the recognition task [7] [8].

The CNN-LSTM (CNN-Long Short-Term Memory) method has been proposed by Rima Tri Wahyuningrum to diagnose knee OA severity from X-Ray images. Experimental results on state-of-the-art CNN architectures revealed that the VGG-16 model extracts the high-level feature representations. These allows the LSTM model to distinguish KL between grades 0 - 4 efficiently and it is is used to differentiate the severity of osteoarthritis (OA). The future enhancement could be applying this work to the segmentation challenge by developing a model which can accurately predict the pixel labels for JSN with a small quantity of training data set [9].

Yifan Wang demonstrated a deep learning-based highly automatic technique for diagnosing osteoarthritis. Transfer learning from the object detection domain was successfully applied to the segmentation of the knee joint area. A model trained on 4.43 percent of annotated data can extract accurate ROIs (Region of interest) from over 4500 samples in the remaining data. Author has used the visual transformation to exploit correlations between different parts of the original X-Ray image for the OA severity categorization. Experiment findings suggest that the proposed method outperforms previous state-of-the-art methods in terms of OA severity categorization, as shown in Table I [5].

TABLE I. Results of Wang's experiment using different models/methods for knee osteoarthritis.

Model	Accuracy (%)
VGG-19	53.40
ResNet50	66.68
ResNet101	66.70
Ordinal loss (ResNet-50)	66.20
Ordinal loss (ResNet-101)	65.50
Siamese net	66.71
Wang's method	**69.18**

Josheph Antony's has looked into numerous new ways for applying CNNs to automatically quantify knee OA severity. The initial step is used to pinpoint the location of the knee joint. As an alternative to template matching, author has proposed training a linear SVM (Support Vector Machine) using horizontal picture gradients, which is more accurate and as well as faster. Antony has mentioned in his study that, using KL grades as a continuous variable and assessing accuracy using mean squared error is preferable. This method allows the model to be trained using regression loss. This discourages errors proportionally to their severity, which results in to more accurate predictions. Another advantage of this method is that it allows predictions to fall between grades, which corresponds to a continuous disease development [10].

The most of the models available for deep learning cannot reach above 70% validation accuracy. At a same time it is more significant that how pre-possessing a particular data-set is applied. Most of the author in their study in the literature have used standard KL Classification for severity grading for knee osteoarthritis. In this paper, the author has compared the ResNetv2, VGG, and Xception models of deep learning and proposed model having comparable results as compared to state-of-the-art literature. The trained model is being ported to NVIDIA Jetson-Nano board. The developed API for email communication received input image over email, do the diagnosis and generates report based on diagnosis.

3. The Proposed Model for Knee OA Diagnosis

The software model for Knee OA is described in this section. Based on the literature review, three models have been designed, implemented and tested. Firstly, the description of data-set is presented followed by discussion on pre-processing of of data-set is discussed. The classification of machine learning for Knee OA is explained, which is being used to select the best algorithm for prediction. The fourth part is to explaining about the development of an Email API for communicating with users and servers for patient's images and reports generation. The description of implementation on hardware is given in section 4.

The basic system level block diagram is shown in Figure 1. As shown in the Figure 1, the Email and Mobile communication are used for input to the system and generated report as output of the system. The system consists of training data-set, feature extraction or pre-processing, machine learning Algorithm, and Trained model. The entire system is ported on stand alone controller board (Jetson Neno).

A. Description of Data-set being used for implementation

Kellgren and Lawrence classification: For Knee Osteoarthritis, there is a standard Kellgren and Lawrence classification for osteoarthritis, which is classified based on the severity of osteoarthritis in different 5 classes [11] as shown in the Figure 2. The description of the various grades/classes are given as below:

- Grade 0 (none): is healthy or without any defect with no X-Ray changes of osteoarthritis
- Grade 1 (doubtful): is potential osteophytic lipping (irregular bone formation around the vertebral bodies) and joint space narrowing
- Grade 2 (minimal): is minimal definite osteophytes with possible joint space narrowing
- Grade 3 (moderate): Numerous osteophytes, evident restriction of joint space, significant sclerosis, and likely bone end deformation
- Grade 4 (severe): Large osteophytes, significant joint space restriction, severe sclerosis, and visible deformation of bone endings are all signs.

The data-set that used in this classification comprises of 9786 images. In which every Image is pre-labeled and classified in five different categories (Grades), where each image is of size 224x224 pixels with color information. Training data-set is distribution/Classification is shown in the Figure 3. [6].

B. Pre-Processing of Data-Set

First of the entire classified data-set are splitted into Training, Validation, and Testing data-set. For accessing all images, one data frames is created from respective class. Then Train, Test and Validation generator are created in which batch size of images for training and validating decided in ResNetv2 and VGG19 model, where batch size was taken as 60. It is taken as 32 for XceptionNet. Then after the image was converted into the size of 224x224 pixels size, followed by conversion it into RGB2GRAY. After that, The adaptive threshold set down to images for the white and black segmentation. The Images after pre-processing are shown in 4.

After completing above mentioned processing, Data augmentation is applied to the image. In this processing, a random image rotated up to $+/-10^{o}$, Shift the image for some amount, shearing the image, zoom the image, and flip any random image operation that can occur. After these processing the image looks like as shown in Figure 4.

C. Description of Implemented Models

Initially, three machine learning models ResNetv2, VGG19, and XceptionNet are being implemented. Based on the comparative analysis of the results for the different models, the best model with the highest validation accuracy with modification is implemented on the Jetson Nano Hardware controller board.

1) (Residual Networks-2 (ResNetv2) Model

Basic Architecture of ResNetv2 model is shown in the Figure 5 [12]. The convolutional neural network Inception-ResNet-v2 was trained on over a million photos from the ImageNet database. The 164-layer network can identify photos into 1000 object categories, including keyboards, mice, pencils, and a variety of animals. As a result, the network has learned a variety of rich feature representations for a variety of images. The network has an input image input of size 224X224 [8], [13].

2) Visual Geometry Group-19 (VGG-19) Model

The VGG19 model is a variation of the VGG model with 19 layers (16 convolution layers, three fully connected layers, 5 MaxPool layers, and 1 SoftMax layer) which is shown in Figure 6 [14]. Other VGG variations include VGG11, VGG16, and many more. There are 19.6 billion FLOPs in VGG19 [15], [16]. A 224x224 RGB image is used as the input to the VGG-based convNet. The pre-processing layer subtracts the mean image values derived for the complete ImageNet training set from the RGB image with pixel values in the range of 0–255.

After pre-processing, the input images are transmitted via these weight layers. A stack of convolution layers is used to process the training images. In the VGG16 architecture, there are 13 convolutional layers and three fully linked layers. Instead of huge filters, VGG uses smaller (3x3) filters with more depth. It has same functional receptive field as if only one 7x7 convolutional layer were used. Another VGGNet variant includes 19 weight layers, including 16 convolutional layers, three fully connected layers, and the same five pooling layers. VGGNet has two completely connected layers with 4096 channels each, followed by another fully connected layer with 1000 channels to predict 1000 labels in both variations. The Softmax layer is used for categorization in the last fully connected layer.

3) The Architecture of XceptionNet Model

Xception is a Depth wise Separable Convolutions-based deep convolutional neural network architecture as shown in

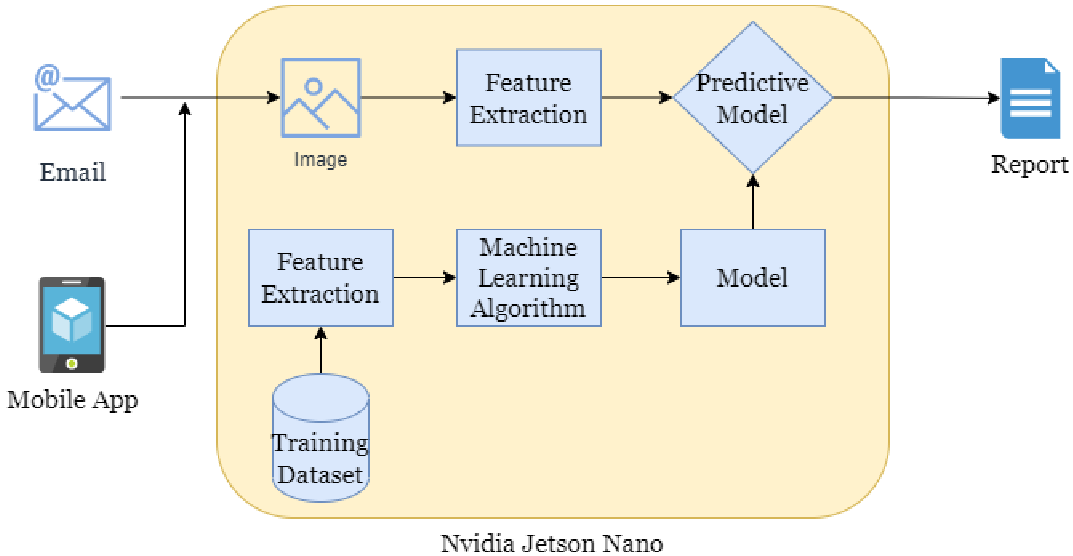

Figure 1. The Basic System level Block diagram

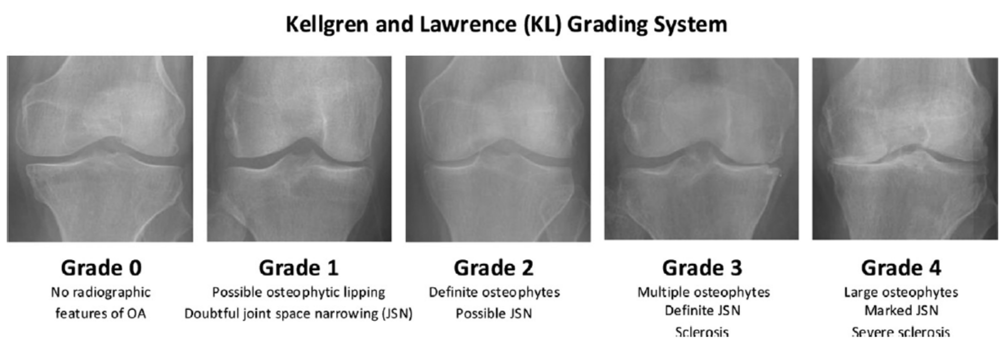

Figure 2. Knee joint sample images of all KL grades and their corresponding criterion[11]

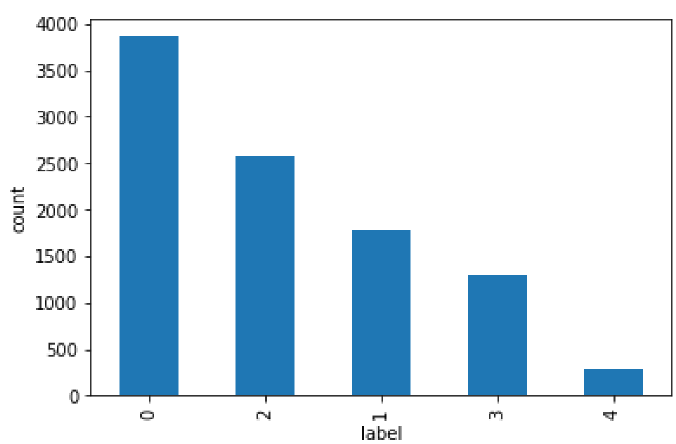

Figure 3. Classification of Images based on Grades

Figure 7 [17]. The Francois Chollet, a Google employee has introduced this network. The "extreme" version of an Inception module is known as Xception [18].

After each convolution and each spatial convolution block, a batch normalising operation is conducted. Each block is assigned a number, with the first indicating the kernel size, the second the number of filters in the block, and the third the convolution step size. The Xception stands for "extreme inception" and it pushes Inception's concepts to their logical conclusion. In Inception, 1x1 convolutions were used to compress the original input, and different types of filters were applied to each of the depth spaces based on the input spaces. The Xception simply reverses this process. Instead, it applies the filters to each depth map individually before compressing the input space using 1x1 convolution across the depth. This method is nearly identical to depth wise separable convolution, a neural network design operation that has been utilized since 2014. One further distinction exists between Inception and Xception [18].

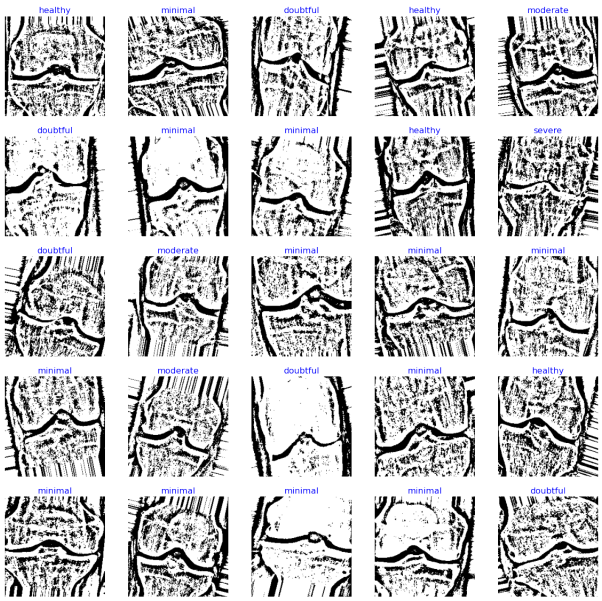

Figure 4. Images after applying Pre-processing

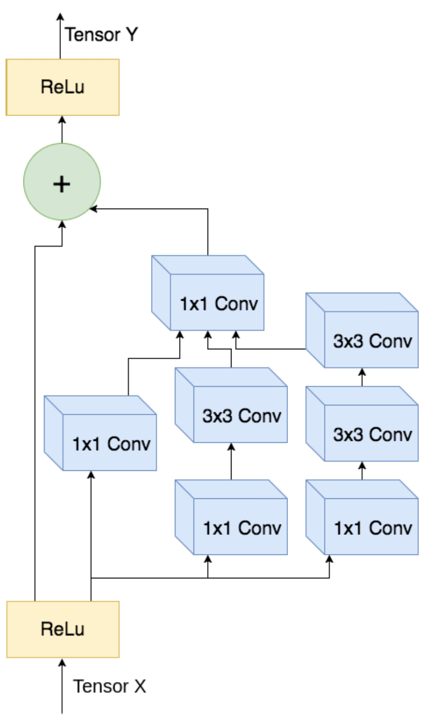

Figure 5. The Architecture of ResNetv2 Model

D. *Application Programming Interface (API) for E-mail communication*

The main communication link between user and system is email communication. The Email API is easy to use user has to send just an image to a specified/particular email id from their email account to the system. The system will automatically extract the attachment and pass it to the predictive model. Based on the analysis, system will generate the report for a given classification. The API is developed using *"Imbox"* by python and it is backed by google. An email API allows programs to access email platform capabilities such as producing and sending transnational emails, modifying templates, and accessing email metrics.

4. The System Implementation on Hardware

The proposed system is trained and optimized model is deployed it on to Xilinx Pynq Field Programable Gate Array (FPGA) board as well as Nvidia Jetson Nano board as final system. The FPGA hardware is more suitable than the GPU as far as the following parameters are concern. As far as the Programming complexity and convenience are concern, the GPU is more easy to use. Also NVIDIA's has it's own Single board GPU Jetson Nano which comprises of GPU. This development board is being used as it has some advantages like Power Efficiency, Processing Power, Programability, Re-Configurablility, Flexibility, Convenience, and ASIC Prototyping.

A. *The System Hardware Introduction: NVIDIA Jetson Nano Board*

The NVIDIA Jetson is a line of embedded computing boards produced by the NVIDIA company. NVIDIA's Tegra processor (or SoC) includes an ARM architecture based central processing unit in the Jetson TK1, TX1, and TX2 models (CPU). The Jetson is a low-power system created to speed up machine learning applications. The Jetson Nano Board is shown in Figure 8.

The Jetson Nano is a 260-pin SODIMM with industry-leading compute capabilities, 64-bit operating capability, and integrated advanced multi-function audio, video, and image processing pipelines, designed for usage in power-constrained environments. Several architectural advancements were incorporated in the Maxwell GPU architecture in order to extract optimum performance per watt used. The Jetson Nano series module includes these core components (NVIDIA® Tegra® X1 series SoC, NVIDIA Maxwell GPU, ARM® quad-core Cortex®-A57 CPU Complex, 4GB LPDDR4 memory, 16GB eMMC 5.1 storage, Gigabit Ethernet (10/100/1000 Mbps), PMIC, regulators, power and voltage monitors, 260-pin keyed connector (exposes both high-speed and low-speed industry standard I/O), and On-chip temperature sensors).

B. *The System Hardware setup*

As shown in Figure 9, Single stand alone NVIDIA Jetson Nano board is connected with Ethernet and containing Pre-trained model ready to predict result where input image is received through an email API and report will generate through system after prediction which will be sent it to sender.

5. Implementation Results of Different Model

The Comparative results of different software model, Where individual Results for ResNetv2 , VGG-19 and Enhanced XceptionNet model are generated are discussed and demonstrated in this section.

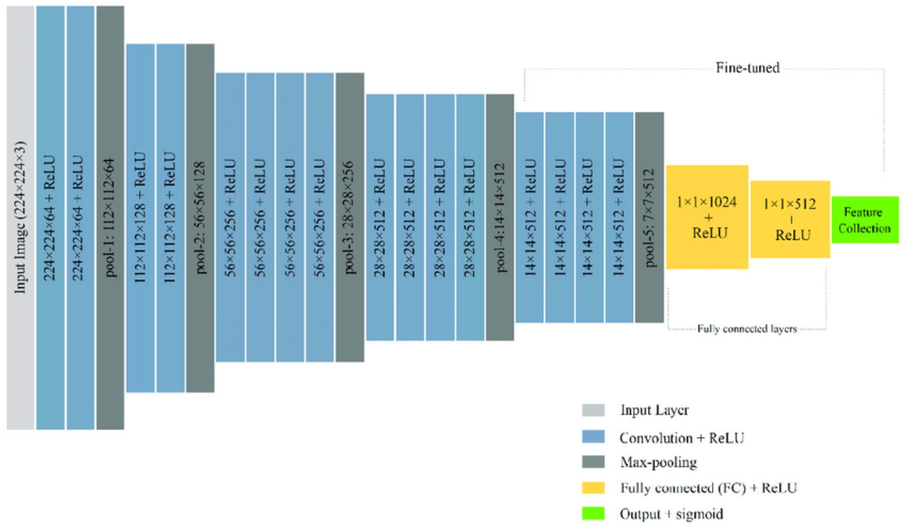

Figure 6. The Architecture of VGG-19 Model

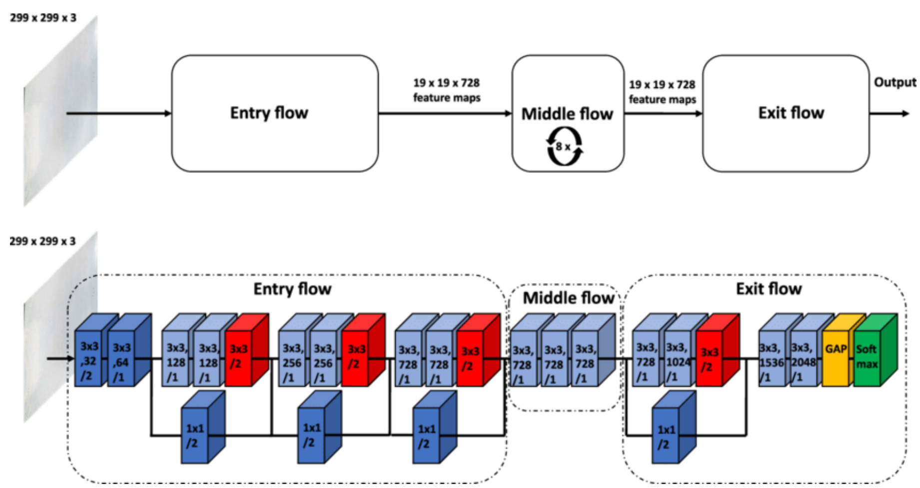

Figure 7. The Architecture of XceptionNet Model

A. The ResNetv2 Model Results

The Figure 10 shows training and validation loss. It is demonstrated that during exercise (red color), the loss decreases every epoch, and it is lowest at the last epoch. The validation loss is not linear, it has spiked in loss, indicating that proper validation is not done but catches up as a subsequent epoch.

The training and validation accuracy are shown in the Figure 11. It has been observed that during training (red color), accuracy increases every epoch, and it is highest at the 11th epoch. The validation accuracy is not linear, it has spiked in accuracy, which indicates that it has some difficulty predicting a proper classification during validation. However, it catches up as a subsequent epoch.

The Table II shows the results of classification report for ResNetv2 model which contains precision, Recall, f1 score for each classes. Here we can observer that minimal class has 68%, healthy has 56%, moderate has 52%, doubtful has 68%, and most important, severe has 75% precision in testing. Overall ResNetv2 accuracy is 64%. Here f1 score of the severe class is 77% which is better than all classes. It can be concluded that the model can predict severe cases better than any other class.

The Figure 12 shows confusion matrix. This is used for multi-class classification. The confusion matrix shows true positive, false-positive, false negative, and true negative for every class. It can be observed that the false positive and true negatives values are higher in some classifications.

B. The VGG-19 Model Results

Figure 13 is shows training and validation loss for VGG-19 model. The figure clearly shows that during training (red color), the loss decreases every epoch and is lowest at the

Figure 8. The NVIDIA Jetson Nano Board[19]

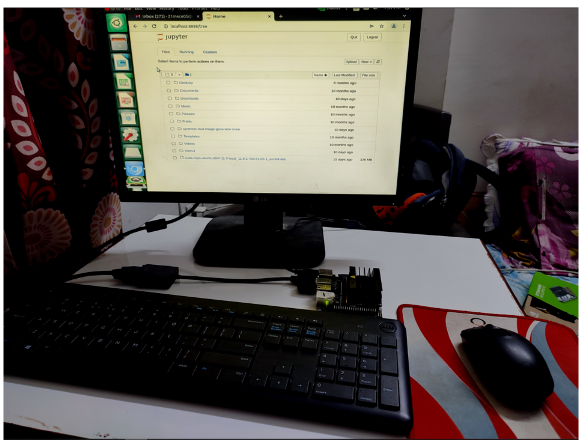

Figure 9. The Hardware Setup of the System

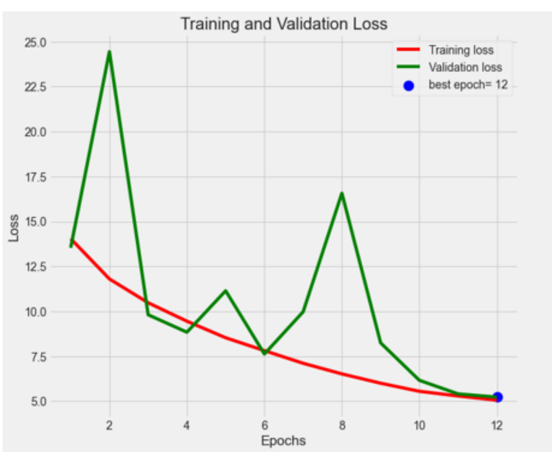

Figure 10. The ResNetv2 training and validation loss

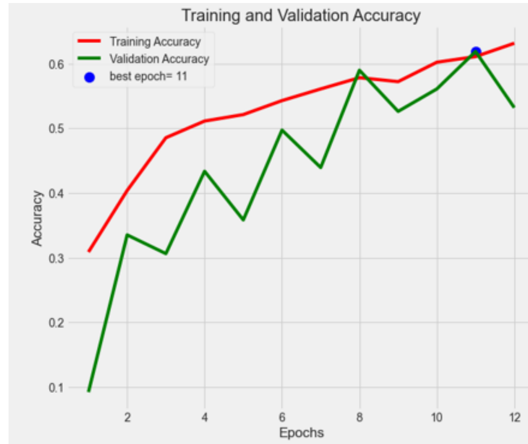

Figure 11. The ResNetv2 training and validation accuracy

TABLE II. The ResNetv2 Model Classification Report

Classification Report:				
	precision	**recall**	**f1-score**	**support**
minimal	0.68	0.79	0.73	71
healthy	0.56	0.64	0.60	53
moderate	0.52	0.28	0.36	40
doubtful	0.68	0.75	0.71	28
severe	0.75	0.62	0.77	8
accuracy		**0.64**		200
macro avg	0.69	0.62	0.63	200
weighted avg	0.63	0.64	0.62	200

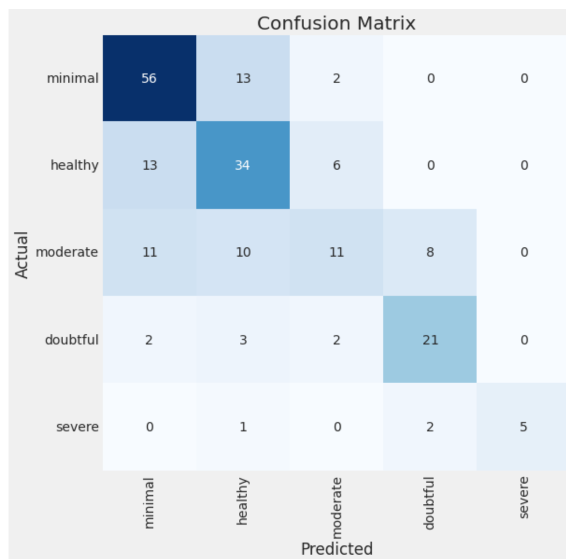

Figure 12. The Confusion Matrix for ResNetv2 based Model

last epoch. Here validation loss is not linear, it has spiked in loss, indicating that proper validation is not done but catches up as a subsequent epoch, but after sixth epoch validation loss has not been improved.

The Figure 14 is shows training and validation accuracy for VGG-19 model. The is is clearly observed that during training (red color), accuracy increases every epoch, and it is highest at the 112th epoch. However validation accuracy

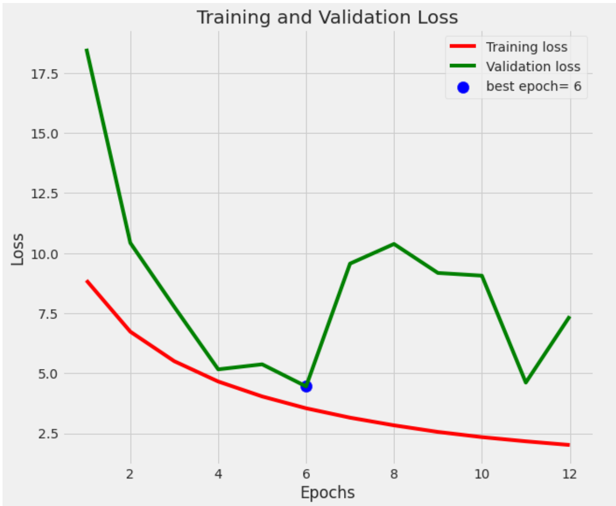

Figure 13. The VGG-19 Model training and validation loss

is not linear, it has spiked in accuracy, which indicates that it has some difficulty predicting a proper classification during validation. However, it couldn't catches up in subsequent epochs and stays constant.

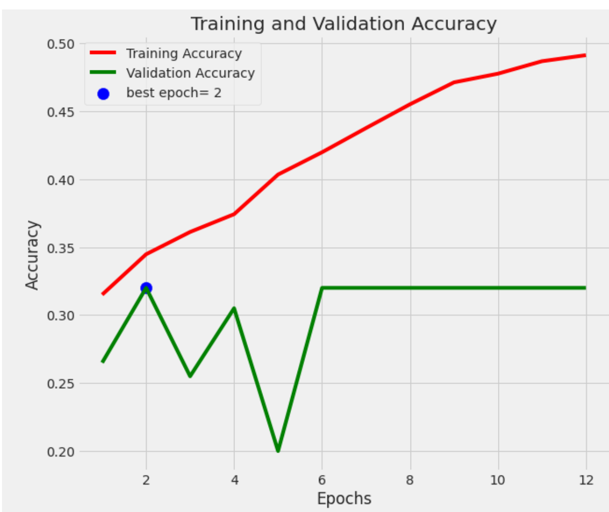

Figure 14. The VGG-19 Model Training and validation accuracy

The Confusion matrix is shown in the Figure 15, which uses for multi-class classification. The confusion matrix shows true positive, false-positive, false negative, and true negative for every class. It has been observed that prediction for any classification is too poor.

the Figure shows 15 confusion matrix, which is used for multi-class classification. The confusion matrix shows true positive, false-positive, false negative, and true negative for every class. It shows that the prediction for any classification is too poor.

The Table III is classification report for VGG-19 model

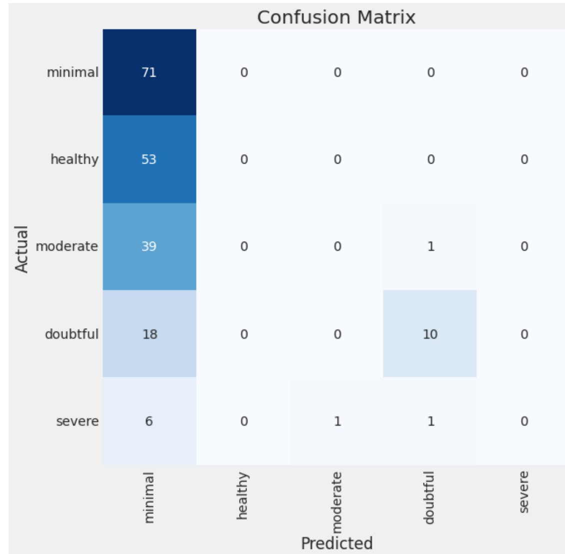

Figure 15. Confusion Matrix for results based on VGG-19 Model

TABLE III. The VGG-19 Classification Report

Classification Report:				
	precision	**recall**	**f1-score**	**support**
minimal	0.38	1.00	0.55	71
healthy	0.00	0.00	0.00	53
moderate	0.00	0.00	0.00	40
doubtful	0.83	0.36	0.50	28
severe	0.00	0.00	0.00	8
accuracy		**0.41**		200
macro avg	0.24	0.27	0.21	200
weighted avg	0.25	0.41	0.27	200

which contains precision, recall, f1 score for each classes. here we can see that minimal class has 38%, healthy has 0%, moderate has 0%, doubtful has 83%, and most important, severe has 0% precision in testing. Overall VGG-19 accuracy is 41%. Here f1 score of three class is zero which shows worst model for training knee osteoarthritis. It is concluded that the model can not predict any cases properly.

C. Enhanced XceptionNet Model Results

Because of worst result of VGG-19 model new XceptionNet finalise to use for that experiment setup also changed. Now it is been train for more number of epoch about 37 epoch. and also number of test data-set is also increase to 783 images in which prediction is significantly improved for all classes as shown in the Figure 16.

The Table IV is classification report for XceptionNet model which contains precision, recall, f1 score for each classes. It is being observed that minimal class has 97%, healthy has 99%, moderate has 94%, doubtful has 99%, and most important, severe has 100% precision in testing and Overall XceptionNet Accuracy is 97%. Here f1 score of

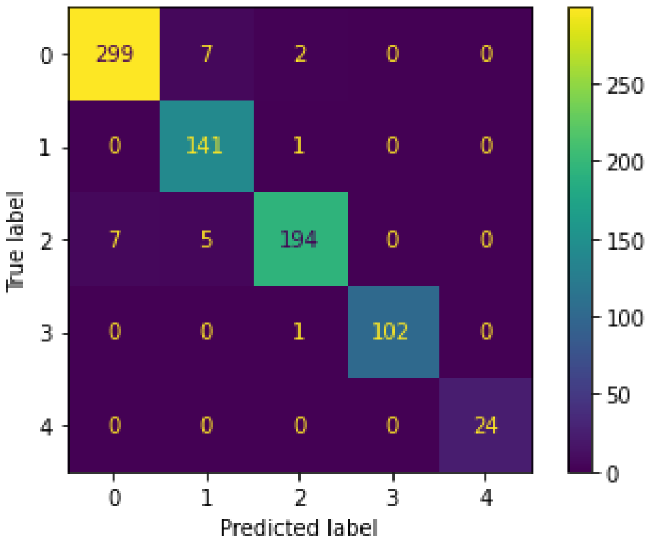

Figure 16. The XceptionNet Confusion Matrix

TABLE IV. The Enhanced XceptionNet Classification Report

Classification Report:				
	precision	**recall**	**f1-score**	**support**
minimal	0.97	0.98	0.97	308
healthy	0.99	0.92	0.95	142
moderate	0.94	0.98	0.96	206
doubtful	0.99	1.00	0.99	103
severe	1.00	1.00	1.00	24
accuracy		**0.97**		783

the severe class is 100% which is the best in all model. It is being observed that this model can predict severe cases better than other two method.

D. The Comparative analysis

The final comparative analysis is being shown in V. It is being observed that by using Enhanced XceptionNet model accuracy of 97% can be achieved. This is very much acceptable for any medical application. Therefore in hardware implementation of the system the modified Xception model is used.

TABLE V. Comparative analysis

	Accuracy
ResNetv2	0.64
VGG-19	0.41
Enhanced XceptionNet	**0.97**

E. Real time working of Application

The Figure 17 shows that an email is being sent from client side to the system to particular Email-ID with specific subject line. By that subject line, email API downloads the attachment and passes through system application program.

The input to the system is shown in the figure 18 and and output predictions is shown in the Figure 19 as classification of 4 (severe).

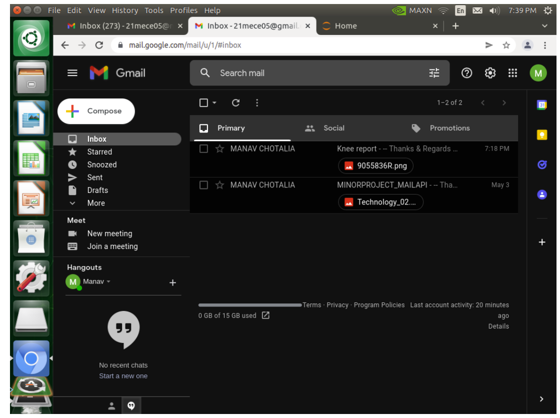

Figure 17. Received Email with specific subject line

Figure 18. Input Test Image

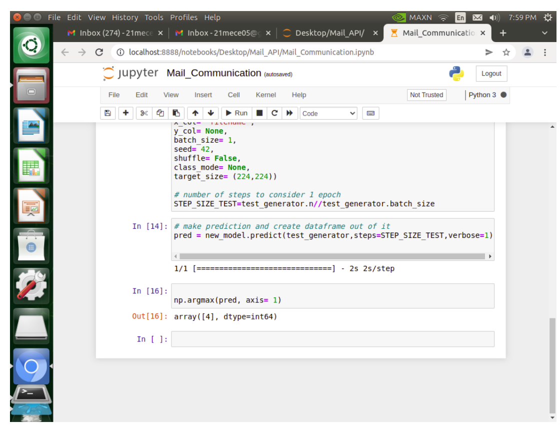

Figure 19. Predicted output as image classification severe

6. Conclusion

Implemented Knee osteoarthritis classification prediction using ResNetv2, VGG-19, and XceptionNet model Architecture. The ResNetv2 model has an accuracy of 64 %, VGG-19 has the worst accuracy of 41%, and the XceptionNet model has the highest accuracy of 97%. In medical applications, prediction accuracy less than 95%

is not acceptable. The final system is implemented using Enhanced XceptionNet model. The trained model is ported on on the NVIDIA Jetson Nano board and the system made autonomous using Email API development. This developed Email API works as communication link between user and system. After sending an Email to system which working on stand alone hardware platform, system do the prediction and returns mail as a diagnosis report to the respective user.

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