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BONE FRACTURE DETECTION USING PRE TRAINED MODEL VGGNET-16

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Abstract: With the advancement of the technology in the medical field doctors need an automated system for analyzing the bone fractures from X rays and recommend medicines. Existing systems can find only on particular type of bones but the proposed system can identify the bone fracture in multiple regions of human body using pre trained models. The main advantage of pre trained models lies in obtaining the optimized weight for each neuron. Out of many existing pre trained models the proposed model utilizes VGGNet-16 because it is a light weight transfer learning system. Using transfer learning the model has achieved 97% accuracy and is greater than 2.9% greater than traditional neural network.

Keywords: Pre-trained Models, VGGNet-16, Neural Networks, optimization, neuron

INTRODUCTION: In present world there are many pre trained models. Pre trained models are sort of neural networks.

1. Neural Networks:

Artificial neurons that get and interpret incoming data make up a neural network. The fully linked layer, the softmax layer, and the convolution layers all receive data. A neural network starts to work when new data is fed into it. The data is then processed via various levels to create the desired outcome. After receiving training from structured input, a neural network produces results.Layers of connected nodes make up a neural network. Neural networks are modeled after how the normal brain processes information and are used to simulate some of the basic functions of the brain. Because of its speedy processing and response times, it is utilized to do a variety of real-time activities.A large number of linked processing components sometimes referred to as Nodes, make up an artificial neural network. These nodes share a connection link with other nodes to connect them. Weights are present in the connection link and these weights contain information about the incoming signal. These weights are updated after every iteration and input. The ultimate inputs of the neural network and its architecture are known as the "trained neural network" after all of the training data examples have been entered. The learning of neural network models is the name of this procedure. To resolve particular issues as outlined in the problem statement, this developed neural network is used. Neutral networks are more effective than humans or basic analytic models and can operate continuously.Additionally, neural networks can be trained to learn from previous results and predict future events based on how closely they resemble previous inputs.

Artificial neural networks can be used to tackle various tasks, such as classification issues, pattern recognition, data clustering, etc. A system needs to have a labeled, directed graph structure with each node performing a straightforward computation to qualify as a NN. A directed graph, as defined by graph theory, consists of a set of nodes, also referred to as vertices, and a set of connections often referred to as edges, that link up pairs of nodes.Each node executes a straightforward calculation. Then, each connection sends a signal—labeled with a weight designating the degree of signal amplification or dilution—from one node to the next.

2. Need of Pre-trained Models:

Pre-trained models are stored networks that have previously undergone training on a sizable dataset, generally for a sizable image-classification task. It takes a lot of time and works to create a model from scratch. You can achieve the same or better results much faster and with a lot less labeled data by using pre-trained models. Pre-trained models are substantially more accurate than convolutional neural networks created from scratch (CNN). Therefore, it would be logical to begin an image identification task using a pre-trained model. Transfer learning applies the knowledge obtained from a model that has already been trained to a different task within the same domain.The idea underlying transfer learning with image analysis is that when a model is taught on a sizable enough dataset with adequate generality, it will be able to represent the visual world as a whole.

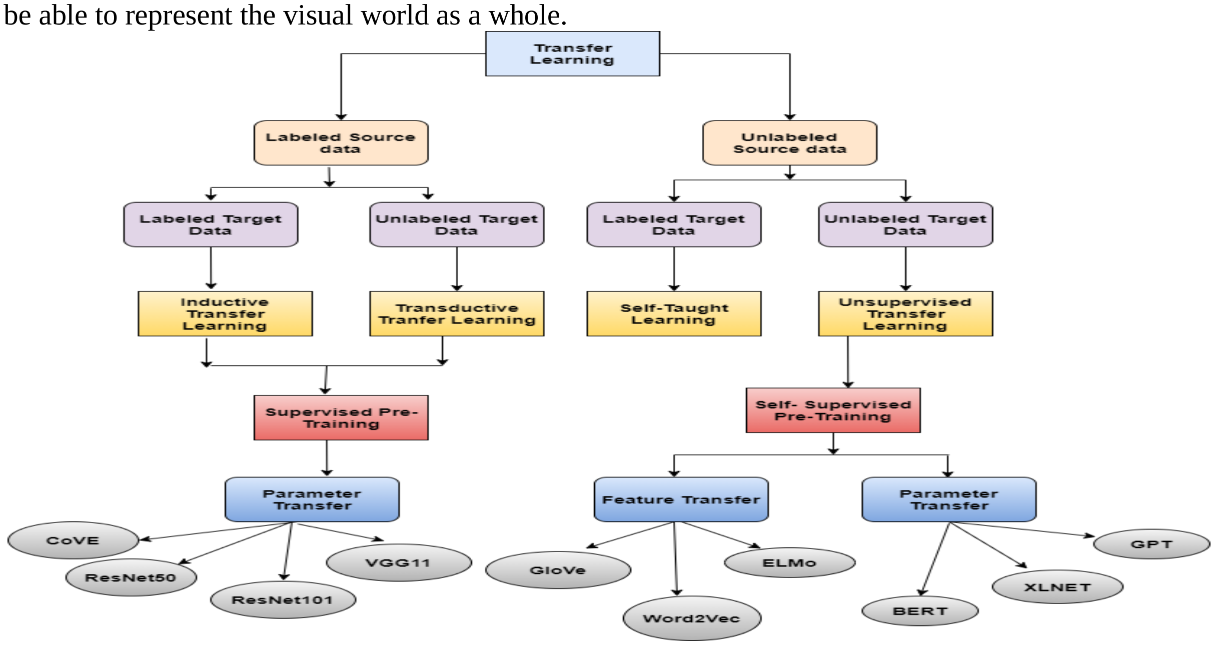


Figure 2: Pre-trained Model Classification

LITERATURE SURVEY:

In [1], Zhihao Dai et al developed a bone X-ray radiography information extraction system based on a disease-causing micro pre-trained Bidirectional Encoder Representations from Transformers (BERT) natural language processing (NLP) model to retrieve the specifics of bone fracture detection and diagnosis. Semi-supervised training was used to develop the model. Only the most popular labels from the dictionary were given to tokens with multiple labels. The authors have also developed a rule-based system that can be defined for automatic annotation to be utilized for learning the developed framework in a loosely supervised approach.The model only evaluated the number, type, and location of bone fractures; however, metadata, such as multiplicity, dimensions, and imaging qualities, might be taken into consideration. If the training dataset was large, scaling up the procedure was difficult due to its inefficiency. There was no assurance that the new regulations were sufficiently broad.

In [2], Hui-ZhaoWu et al suggest the Feature Ambiguity Mitigate Operator (FAMO) model as a technique to reduce feature uncertainty in bone fracture detection on radiographs of diverse body areas. The data labeling was performed in three steps. First, because areas of distinct fractures can overlap when bone frames in viewpoint X-ray images stack on top of one another, Instance segmentation was required rather than segmentation by the doctors. The following are mutilated surface, articular instability, aberrant bone trabecular surface, articular instability, and aberrant bone trabecula are the following, that should have been in a fracture segmentation region were accurately described. The ResNeXt+FPN architecture served as the foundation for the convolutional neural network learning model. The RoI-Align operator can crop features without any distortion. The model was assessed at three different levels: at the case, picture, and fracture levels. The Feature Ambiguity Mitigate Operator (FAMO) methodology was designed to address feature vagueness in gap detection.

In [3], Mengxuan Wang et al proposed the ParallelNet, a brand-new two-stage R-CNN network. A feature fusion connectivity structure and several parallel backbone networks are included.The primary network, which is referred to as the first backbone, uses a typical pooling layer to get characteristics from small cracks. The other backbones, or sub-networks, enlarged the receiver fields for major fracture detection by means of dilated convolution with various dilation rates. To merge the image features, a link structure known as the reverse connection is built between each backbone. The region of interest identifies the area that includes the fracture and is produced using RPN. The RoI pooling layer will scale these ROIs to the same size before computing the classification loss and bounding-box regression for them. The suggested network adopts the feature pyramid structure to identify fractures on various big dimensions. The outcome significantly decreased when the same deformation rates were applied to some other two network infrastructures.

In [4], Rinisha Bagaria et al proposed a Segmentation and classification system using Error Backpropagation Neural Networks and Wavelet Transform. . The image is broken down using wavelet transforms, and the specifics of the vertical, horizontal, and orthogonal components are acquired. SKC uses an iterative process to shorten distances between each object and the centroid of the cluster. The suggested technique Wavelet Transform is an arithmetical tool that can convey messages or images in the subspace as well as frequency domain and denotes image data in multiple resolutions. Some complex images are segmented using the watershed technique since applying a simple median filter and outline detection won't yield excellent and precise results. Threshold-based techniques have the primary flaw that they frequently lack the specificity and sensitivity required for accurate categorization. Using a wavelet-based segmentation technique, the Error Back Propagation Neural Network (EBP-NN) is supplied with the resulting medical pictures. This neural network was evaluated on different other X-ray pictures after being trained using fractured and non-fractured images.

In [5], Bin Guan et al suggested a revolutionary deep learning technique and used it to detect fractures in X-rays of the arm bone. To improve the contrast of original photos, a pixel value transformation and opening operation is devised as part of an image preprocessing technique. To improve the contrast of original photos, a pixel value transformation and opening operation is devised as part of an image preprocessing technique. The suggested approach is a more effective two-stage R-CNN approach. "Anchor" boxes, which serve as benchmarks at scales ranging and dimensions, are introduced in the RPN. At each unit of the feature map, RPN predicts a large number of Regions of Interest simultaneously. All pictures are refined using the geometric folding approach and image pixel transformation to increase image clarity. The reliability of the dataset has a significant impact on the model. If the data collected are of low resolution, the model cannot forecast bone fracture.

In [6], D. P. Yadav and Sandeep Rathor et al created a deep neural network model to distinguish between healthy bones and fractures. a method of flipping and shifting images to create a new photo from the dataset at hand. The quantity of data is minimal. CNN uses a convolution layer to classify the features into cancerous and healthy bones after automatically extracting the feature from the source images. Tensor flow and then a deep learning technique have been presented for long bone, short bone, and plain bone fracture diagnosis. To thoroughly examine the performance, the system requires validation on the bigger data set. To get around the issue of overfitting, the training dataset was expanded. On the dataset, a 5-fold cross-validation was performed. Each layer has the activation function ReLU implemented. The activation functions, Adamax and Softmax, have each been applied to the dense layer one at a time.

Table 1: Analysis over the Existing Approaches

S. No	Author	Method/ Algorithm	Merits	Demerits	Metrics
1.	Zhihao Dai	BERT	rule-based system for annotation and inclusion of NLP.	not scalable and no reliability on results	92.82% F1-Score
2.	Hui-ZhaoWu	CNN with Feature Ambiguity Mitigate Operator (FAMO)	ResNeXt+FPN as base support, accurate results of fracture segmentation region.	unusual classification of images.	85% sensitivity
3.	Mengxuan Wang	ParallelNet using R-CNN	can detect both minor and major fractures, feature pyramid structure to identify fractures	decreased performance if there are any changes in the environment.	87.8% precision
4.	Rinisha Bagaria	Error Backpropagation Neural Network (EBP-NN)	image is made as wavelets, WT is used, and Complex images are also processed.	less sensitivity , uses euclidean distance to identify.	92% accuracy
5.	Bin Guan	two-stage R-CNN approach	RPN finds the RoIs using feature maps.	no results on low resolution images, requires high-definition images.	62.04% average precision
6.	D. P. Yadav	Deep Neural Networks	5-fold validation is performed, and Softmax is applied to the dense layer.	Small dataset, prone to overfit.	92.44% accuracy

PROPOSED METHODOLOGY: The proposed model implements vgg model to train the weights of neurons and performs multi classification

VGG16 NET: Convolutional neural networks, a subset of artificial neural networks, are also referred to as ConvNets. A convolutional neural network is made up of a fully connected layer, several hidden layers, and an output layer. The CNN variation known as VGG16 is among the best artificial intelligence models available in present. VGG16 is a technique for identifying and categorizing items. The 16 weighted layers are represented by the Sixteen in VGG16. VGG16 consists of 21 layers altogether—13 convolutional, 5 Max Pooling, and 3 Dense—but only 16 of them are weight layers or the layer for learnable parameters. If conditioned with random weight initialization, VGG16 training can take a while. The relatively homogeneous architecture of VGGNet-16 is appealing. It has several filters but only 3x3 convolutions, like AlexNet.

VGGNet's millions of parameters can be a challenging to work on. The use of transfer learning permits VGG. When the model has been pre-trained on a dataset, the variables are updated for greater precision and the input variables can be used. Innovative item identification models are built using the VGG architecture. The VGGNet, a deep neural network designed for a variety of applications and data outside of ImageNet, outperforms benchmarks. Small, 3 x 3 filtering arrays are used by the network. The overall architecture of the transfer learning is shown in the figure x

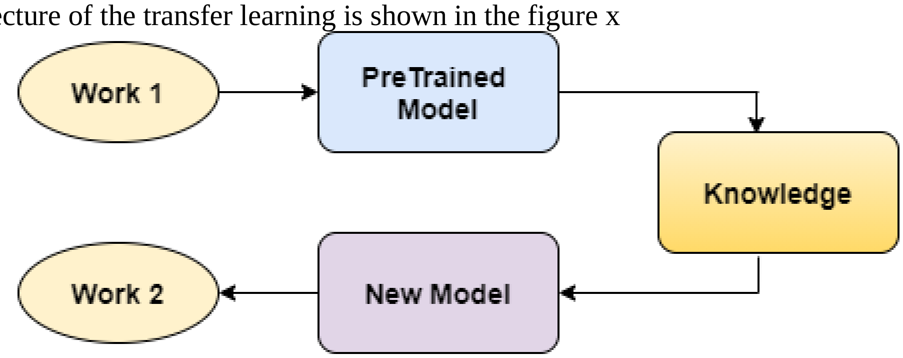


Figure X: Transfer Learning Architecture

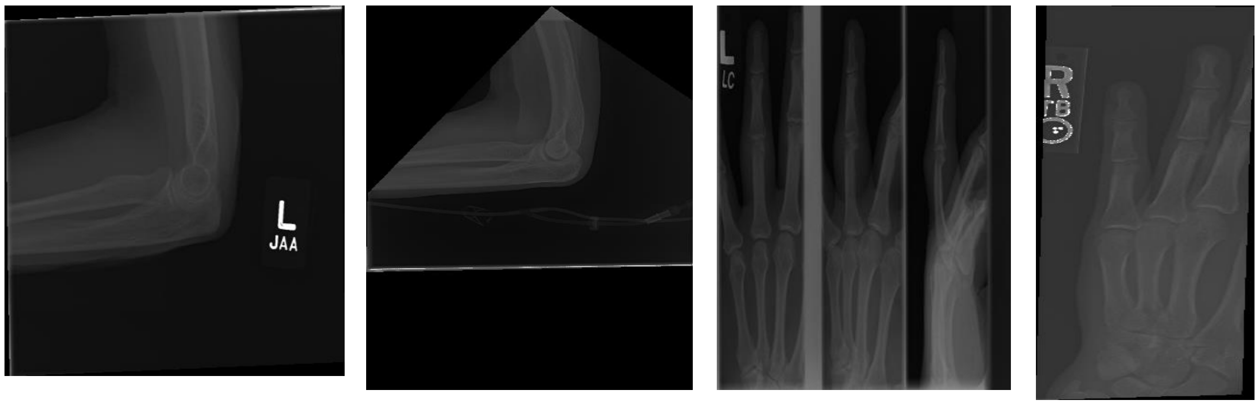
Using transfer learning the last layers of the VGGNET can be customized for improving the performance of the model. The model implements adam optimizer instead of RMSprop. Similarly it implements alternatively sigmoid and relu activation functions

Adam Optimizer: Adaptive moment estimation is a technique for gradient descent optimization. The approach works well when dealing with intricate issues requiring lots of variables or data. It works well and doesn't take up much memory. Intuitively, it combines the momentum algorithm with the RMSP approach and gradient descent. The Adam Optimizer draws on the two approaches' good qualities and strengths to produce a more optimal gradient descent. It measures the learning rate including squared gradients, as RMSprop, and, like SGD with momentum, it employs momentum with the help of gradient's arithmetic mean than the gradient itself, like SGD. Adam is the name of the optimizer, which adjusts the proportional gain for each neural network weight by estimating the first and foremost moments of the gradient. This approach is really simple, simple to use, and uses less memory.

Sigmoid Activation: The neural network's output, such as yes or no, is chosen using an activation function. The obtained values are mapped between 0 and 1 or -1 and 1, etc. The model may easily generalize or adapt to a range of variables and distinguish between the output thanks to non-linear activation functions. In machine learning, the sigmoid function serves as an activation function, which is used to introduce non-linearity into a model. Which value is output and which is not output is decided by the function. It is particularly utilized in models when the output must be a probability prediction.

ReLu Activation: ReLu is a symmetric linear function that produces one as the input if it is positive, and zero if the input is negative. It has developed into the typical activation function for numerous various kinds of neural networks for the reason that a model which utilizes it is the easiest method to train and typically shows better performances. The activation function of a neural network is responsible for converting the summed weighted input of a node into network stimulation or outcome for just that input. Since the ReLu model converged quickly during training, it uses a lot less time.

DATASET DESCRIPTION: The proposed has implemented model on the MURA medical, which can analyze the bone fractures of elbow, finger, forearm, hand, humerus, shoulder, and wrist. Sample images are presented in figure x



Elbow with no fracture **Elbow with fracture** **Fingers with no fracture** **Fingers with fracture**

Figure X: Sample images of bone fractures

RESULTS & DISCUSSION:

```
Epoch 1/15
172/172 [==============================] - 555s 3s/step - loss: 0.1542 - accuracy: 0.9358 - val_loss: 0.1298 - val_accuracy: 0.9400
Epoch 2/15
172/172 [==============================] - 55s 319ms/step - loss: 0.0615 - accuracy: 0.9772 - val_loss: 0.1012 - val_accuracy: 0.9700
Epoch 3/15
172/172 [==============================] - 55s 318ms/step - loss: 0.0298 - accuracy: 0.9901 - val_loss: 0.0471 - val_accuracy: 0.9800
Epoch 4/15
172/172 [==============================] - 55s 319ms/step - loss: 0.0333 - accuracy: 0.9860 - val_loss: 0.1115 - val_accuracy: 0.9700
Epoch 5/15
172/172 [==============================] - 55s 318ms/step - loss: 0.0154 - accuracy: 0.9936 - val_loss: 0.0546 - val_accuracy: 0.9800
Epoch 6/15
172/172 [==============================] - 55s 318ms/step - loss: 0.0060 - accuracy: 0.9982 - val_loss: 0.2061 - val_accuracy: 0.9700
Epoch 7/15
172/172 [==============================] - 55s 318ms/step - loss: 0.0032 - accuracy: 0.9994 - val_loss: 0.2550 - val_accuracy: 0.9700
Epoch 8/15
172/172 [==============================] - 55s 319ms/step - loss: 0.0016 - accuracy: 0.9994 - val_loss: 0.0865 - val_accuracy: 0.9700
Epoch 9/15
172/172 [==============================] - 55s 321ms/step - loss: 2.2578e-04 - accuracy: 1.0000 - val_loss: 0.0655 - val_accuracy: 0.9700
Epoch 10/15
172/172 [==============================] - 56s 323ms/step - loss: 1.3669e-04 - accuracy: 1.0000 - val_loss: 0.1973 - val_accuracy: 0.9700
Epoch 11/15
172/172 [==============================] - 55s 323ms/step - loss: 9.5215e-05 - accuracy: 1.0000 - val_loss: 0.1392 - val_accuracy: 0.9700
Epoch 12/15
172/172 [==============================] - 55s 322ms/step - loss: 3.4466e-05 - accuracy: 1.0000 - val_loss: 0.1430 - val_accuracy: 0.9700
Epoch 13/15
172/172 [==============================] - 56s 324ms/step - loss: 2.3899e-05 - accuracy: 1.0000 - val_loss: 0.1482 - val_accuracy: 0.9700
Epoch 14/15
172/172 [==============================] - 55s 322ms/step - loss: 1.7846e-05 - accuracy: 1.0000 - val_loss: 0.1550 - val_accuracy: 0.9700
Epoch 15/15
172/172 [==============================] - 56s 323ms/step - loss: 1.4953e-05 - accuracy: 1.0000 - val_loss: 0.1612 - val_accuracy: 0.9700
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Figure X: Epochs with training and validation accuracy

Figure x represents the training accuracy and validation accuracy for every epoch. The training accuracy has reached 100% accuracy approximately after half of the iteration and validation accuracy is 97.5% on an average

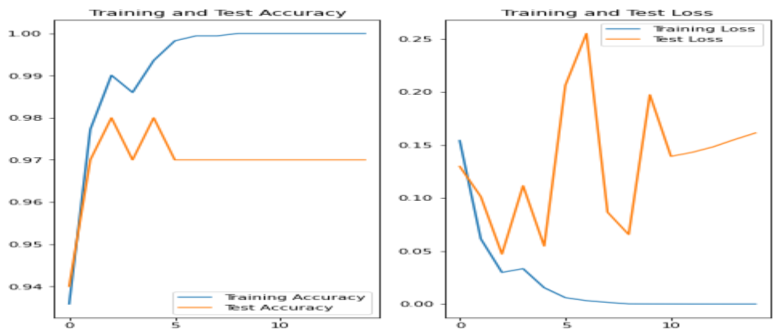

Figure X: Accuracies & Losses Graph

Figure X denotes the plotting values for accuracy and loss for each epoch. Accuracy graph has exhibited the increasing tendency but the loss graph on the validation dataset has increasing tendency instead of decreasing tendency

CONCLUSION: Medical diagnosis of the bone fractures is critical and expensive. The deep learning applications for the identification of fractures make the process fast and less expensive because of the availability of more training data but the proposed model suffers from over fitting and has more loss with the increase in number of epochs. In future work, the model can over come this problem by training with the augmented images.

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