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Detection And Categorization of Acute Disease As Well As Facial Indicators Of Illness Using CNN

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Abstract
Facial and bodily cues in Deep learning (DL) models improve the assessment of patients' health status, as shown in genetic syndromes and acute coronary syndrome.In this study, we developed a computer-aided diagnosis system for automatic Rug sick detection using Facial Cue of illness images.Our findings suggest that facial cues associated with the skin, mouth and eyes can aid in the detection of acutely sick and potentially contagious people.We employed deep transfer learning to handle the scarcity of available data and designed a Convolutional Neural Network (CNN) model along with the four transfer learning methods: VGG16, VGG19, InceptionV3, Xception and ResNet50.The proposed approach was evaluated on publicly available Facial Cue of illness dataset

Introduction
Acutely sick people were rated by naive observers as having paler lips and skin,more swollen face, droopier corners of the mouth, more hanging eyelids,redder eyes, and less glossy and patchy skin, as well as appearing more tired.[1].Our findings suggest that facial cues associated with the skin, mouth and eyes can aid in the detection of acutely sick and potentially contagious people[2].Humans can adopt a facial expression voluntarily or involuntarily, and the neural mechanisms responsible for controlling the expression differ in each case[3].Voluntary facial expressions are often socially conditioned and follow a cortical route in the brain. Conversely, involuntary facial expressions are believed to be innate and follow a subcortical route in the brain[4].Facial recognition is often an emotional experience for the brain and the any data is highly involved in the recognition process. There is controversy surrounding the question of whether facial expressions are worldwide and universal display among humans. Supporters of the Universality Hypothesis claim that many of the facial expressions are innate and have roots in evolutionary ancestors[5].Responding appropriately to gaze cues is essential for fluent social interaction, playing a crucial role in social learning, collaboration, threat assessment and understanding others' intentions, previous research has shown that responses to gaze cues can be studied by investigating the gaze-cuing effect (i.e. the tendency for observers to respond more quickly to targets in locations that were cued by others' gaze than to uncured targets)[6].A recent study demonstrating that macaques demonstrate larger gaze-cuing effects when viewing dominant conspecifics than when viewing subordinate conspecifics suggests that cues of dominance modulate the gaze-cuing effect in at least one primate species[7].Moreover, this effect of facial masculinity on gaze cuing decreased as viewing time was increased, suggesting that the effect is driven by involuntary responses.[8]Our findings suggest that the mechanisms that underpin reflexive gaze cuing evolved to be sensitive to facial cues of others' dominance, potentially because such differential gaze cuing promoted desirable outcomes from encounters with dominant individuals.[9]

Related Work
1. Material and Methods:
1.1 Dataset
Photos from gathered from "imagenet" collection of people whose facial features were manipulated to resemble a state of acute illness were used to extract features of illness and generate a synthetic dataset of acutely ill photographs, using a convolutional neural network (CNN) for data augmentation.

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Then, five distinct CNNs were trained on different parts of the facial photographs and concatenated into one final, stacked CNN which classified individuals as healthy or acutely ill.
The table shows the partitioning dataset table. This shows the data partitioning the training and testing . Actually the data contains the training data
Will (60%) of objects. Testing dataset contains the(40%) of objects).

Image name	Training	Testing	Total
Mouth	240	96	336
Nose	200	80	280
Skin	300	120	420
Eye	200	80	280
Stacked	100	40	140
Total	1040	416	1456

2. Algorithm

In deep learning, a convolutional neural network is a class of deep neural networks, most commonly applied to analyzing visual imagery.A convolutional neural network consists of an input layer, hidden layers and an output layer. In any feed-forward neural network, any middle layers are called hidden because their inputs and outputs are masked by the activation function and final convolution. In a convolutional neural network, the hidden layers include layers that perform convolutions. Typically this includes a layer that does multiplication or other dot product, and its activation function is commonly ReLU. This is followedby other convolution layers such as pooling layers, fully connected layers and normalization layers.

VGG16:

The VGG network architecture was introduced by Simonyan and Zisserman in their 2014.This network is characterized by its simplicity, using only 3×3 convolutional layers stacked on top of each other in increasingdepth. Reducing volume size is handled by max pooling. Two fully-connected layers, each with 4,096 nodes are then followedby a Softmax classifier. The “16” stand for the number of weight layers in the network.

VGG19:

VGG is a convolutional neural network which has a depth of 19 layers. It was build and trained by Karen Simonyan and Andrew Zisser man at the University of Oxford in 2014.VGG Net has 19 weight layers consisting of 16 convolutional layers with 3 fully connected layers and same 5 pooling layers. In both variation of VGG Net there consists of two Fully Connected layers with 4096 channels each which is followed by another fully connected layer with 1000 channels to predict 1000 labels. Last fully connected layer uses soft max layer for classification purpose, but made feasible due to the utilization of graphics processing units (GPUs) during training.

ResNet50:

ResNet50 is a convolutional neural network which has a depth of 50 layers. It was build and trained by Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun in their 2015 and you can access the model performance results on their paper, titled Deep Residual Learning for Image Recognition.This model is also trained on more than 1 million images from the Image Net database. Just like VGG-19, it can classify up to 1000 objects and the network was trained on 224x224 pixels colored images. Here is brief info about its size and performance.

InceptionV3:

It is a convolutional neural network for assisting in image analysis and object detection, and got its start as a module for Google net. It is the third edition of Google’s Inception Convolutional Neural Network, originally introduced during the Image Net Recognition Challenge. The design of Inceptionv3 was intended to allow deeper networks while also keeping the number of parameters from growing too large: it has “under 25 million parameters”.Just as Image Net can be thought of as

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a database of classified visual objects, Inception helps classification of objects in the world of computer vision. The Inceptionv3 architecture has been reused in many different applications often used "pre-trained" from Image Net. One such use is in life sciences.

Xception:

Xception Model is proposed by Francois It's an extension of the inception Architecture which replaces the standard Inception modules with depth wise Separable Convolutions. This observation leads them to propose a novel deep convolutional neural network architecture inspired by Inception, where Inception modules have been replaced with depth wise separable convolutions.It expensive to train, but are pretty good improvements compared to Inception. Transfer learning brings part of the solution when it comes to adapting such algorithms to your specific task.

3. Result:

This Table shows the statistical data analysis table. This table shows the sensitivity, specificity, PPV(positive predictivevalue),NPV(negative predictive value)percentages values for the images of mouth, nose, skin, eye, stacked.

Image name	Sensitivity(%)	Specificity(%)	PPV(%)	NPV(%)
Mouth	84.2	57.9	66.7	78.6
Nose	89.4	42.1	60.7	80.0
Skin	10.5	94.7	66.7	51.4
Eye	63.2	57.9	60.0	61.1
Stacked	100	42.1	63.3	100

The Table shows the percentages table. This table shows the image-wise accuracy levels with different models like CNN, TLM,RSN. The accuracy levels will be calculating based on objects of training and testing datasets. finally Separately total accuracyvalues will be shown in the table with model wise.

Image name	CNN(accuracy value%)	TLM(accuracy value%)	RSN(accuracy value%)
Mouth	85	72	65
Nose	82	74	68
Skin	81	74	69
Eye	84	76	61
Stacked	85	72	66
Total	83.4	73.6	65.8

4. Conclusion:

In this project we have successfully classified the images of Facial Cue images of a person, is either affected with the Facial Cue illness or not using the deep learning. Here, we have considered the dataset of Facial Cue images which will be of 2 different types (Facial Cue illness affected and normal) and trained using CNN along with some of the transfer learning methods. After the training we have tested by uploading the image and classified it.This can be utilized in future to classify the types of different infections easily that which can tend to easy to find out the infections in early stages and can be cured in the initial stages only.

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