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IDENTIFICATION OF ACUTE ILLNESS AND FACIAL CUES ILLNESS USING CONVOLUTION NEURAL NETWORK

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Abstract: Facial and bodily cues (clinical gestalt) in Deep learning (DL) models improve the assessment of patients' health status, as shown in genetic syndromes and acute coronary syndrome. It is unknown if the inclusion of clinical gestalt improves classification of acutely ill patients. As in previous research in DL analysis of medical images, simulated or augmented data may be used to assess the usability of clinical gestalt. In this study, we developed a computer-aided diagnosis system for automatic Rug sick detection using Facial Cue of illness images. Acutely sick people were rated by naive observers as having paler lips and skin, a 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. 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. Where, in the existing methods ResNet101 is used that which did not got the proper accuracy and that tend to be improved. Hence the present method with other transfer learning methods is proposed. The proposed approach was evaluated on publicly available Facial Cue of illness dataset.

***Index Terms* - Rug healthy, Rug sick, Facial Cue of illness images. Deep Learning, CNN, VGG16, VGG19, InceptionV3, Xception and ResNet50.**

I. INTRODUCTION

Acutely sick people were rated by naive observers as having paler lips and skin, a 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. 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 Facial appearance correlates with leadership, both in terms of who is chosen (leader selection) and how they do (leader success). Leadership theories suggest that exceptional individuals acquire positions as leaders. Exceptional traits can differ between domains, however, and so the qualities valued in leaders in one occupation may not match those valued among leaders in another. To test this, we compared the relationship between facial appearance and leadership across two domains: law firms and mafia families. Perceptions of power correlated with leadership among law executives whereas social skill correlated with leadership in organized crime. Critically, these traits were distinctive within their respective groups. Furthermore, an experimental test showed that the relative frequency of facial traits in a group can render them either an asset or liability. Perceived leadership ability is therefore enhanced by characteristics that appear unique among individuals who satisfy the basic criteria for their group.

Humans can adopt a facial expression voluntarily or involuntarily, and the neural mechanisms responsible for controlling the expression differ in each case. 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 sub cortical route in the brain.

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 a worldwide and universal display among humans. Supporters of the Universality Hypothesis claim that many facial expressions are innate and have roots in evolutionary ancestors. Opponents of this view question the accuracy of the studies used to test this claim and instead believe that facial expressions are conditioned and that people view and understand facial expressions in large part from the social situations around them. Moreover, facial expressions have a strong connection with personal psychology. Some psychologists have the ability to discern hidden meaning from a person's facial expression

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). 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. Here, we show a similar effect of facial cues associated with dominance on gaze cuing in human observers: at short viewing times, observers demonstrated a greater cuing effect for gaze cues from masculinized (i.e. dominant) faces than from feminized (i.e. subordinate) faces. Moreover, this effect of facial masculinity on gaze cuing decreased as viewing time was increased, suggesting that the effect is driven by involuntary responses. 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.

II LITERATURE SURVEY

Husabo and Nilsen they started recognition of sepsis is critical for timely initiation of treatment. The first objective of this study was to assess the timeliness of diagnostic procedures for recognizing sepsis in emergency departments. We define diagnostic procedures as tests used to help diagnose the condition of patients. The second objective was to estimate associations between diagnostic procedures and time to antibiotic treatment, and to estimate associations between time to antibiotic treatment and mortality. This observational study from 24 emergency departments in Norway included 1559 patients with infection and at least two systemic inflammatory response syndrome criteria. We estimated associations using linear and logistic regression analyses. Sepsis is a major challenge, being present in a large proportion of hospitalizations that culminate in death. Most sepsis cases seem to arise outside hospital settings, and these patients present to emergency departments with heterogeneous signs and symptoms, making detection and diagnosis challenging. New sepsis criteria and early antibiotic treatment has been a major focus of research and debate over the last years but factors associated with delayed treatment in the emergency departments have received less attention [1].

C,Khoshgoftaar :Deep Learning models have made incredible progress in discriminative tasks. This have been fueled by the advancement of deep network architectures, powerful computation, and access to big data. Deep neural networks have been successfully applied to Computer Vision tasks such as image classification, object detection, and image segmentation thanks to the development of convolutional neural networks (CNNs). These neural networks utilize parameterized, sparsely connected kernels which preserve the spatial characteristics of images. Convolutional layers sequentially down sample the spatial resolution of images while expanding the depth of their feature maps. This series of convolutional transformations can create much lower-dimensional and more useful representations of images than what could possibly be hand-crafted. The success of CNNs has spiked interest and optimism in applying Deep Learning to Computer Vision tasks To build useful Deep Learning models, the validation error must continue to decrease with the training error. Data Augmentation is a very powerful method of achieving this. the augmented data will represent a more comprehensive set of possible data points, thus minimizing the distance between the training and validation set, as well as any future testing sets[2].

Imai and Okami explain about clarifications of cues for age perception. he also analyzed three-dimensional head and face forms of Japanese women. It is known that age-related transformations are mainly caused by changes in soft tissue during adulthood. A homologous polygon model was created by fitting template meshes to each study participant to obtain three-dimensional data for analyzing whole head and face forms. Using principal component analysis of the vertices coordinates of these models, 26 principal components were extracted (contribution ratios >0.5%), which accounted for more than 90% of the total variance. Among the principal components, five had a significant correlation with the perceived ages of the participants ($p < 0.05$). Transformations with these principal components in the age-related direction produced aged faces. Moreover, the older the perceived age, the larger the ratio of age-manifesting participants, namely participants who had one or more age-related principal component score greater than $+1.0\ \sigma$ in the age-related direction. Therefore, these five principal components were regarded as aging factors. A cluster analysis of the five aging factors revealed that all of the participants fell into one of four groups, meaning that specific combinations of factors could be used as cues for age perception in each group. These results suggest that Japanese women can be classified into four groups according to age-related transformations of soft tissue in the face [3].

David Ahmedt-Aristizabal and Clinton: Epilepsy is the most common of the neurological conditions. Mesial temporal lobe epilepsy (MTLE), often with hippo campal sclerosis, is one of the most common causes of drug-resistant epilepsy. Epilepsy surgery has been accepted as an effective treatment for patients with medically refractory epilepsy or whose seizures are nonresponsive to medication. The complete resection of the epileptogenic zone (i.e., the region of the brain that generates epileptic seizures) is the primary goal. Patients with epilepsy exhibit different clinical manifestations based on the underlying networks activated. Semiology has played a pivotal role to provide localizing and lateralizing information in order to allow for successful surgery in addition to neuro physiological and imaging data .While semiology is important, a single sign in isolation is not helpful but rather the progression of events that underlie the integration of various neuronal networks [4].

II. Proposed System

In our proposed method we are performing the classification of either the person is infected with the Facial Cues or not using Convolution Neural Network (CNN) of deep learning along with the transfer learning methods of CNN, which are VGG16, VGG19, InceptionV3, Xception and ResNet50. Early diagnosis of Facial Cues is crucial to ensure curative treatment and using our proposed method. Block diagram of proposed method is shown below increase survival rates.

The figure 1 shows the block diagram of proposed model. This model takes raw dataset as input. This raw data is initially preprocessed so that noisy, uncertainty, duplication of data is cleaned. The preprocessed datasets are partitioned into two subsets namely training, testing. The training subset of dataset is (60%) and testing subset of dataset is (40%) is taken so that it shows good improvement in accuracy. Further, the training subset of dataset is trained using convolutional neural network. The testing subset of dataset is validated using convolutional neural network as a result a

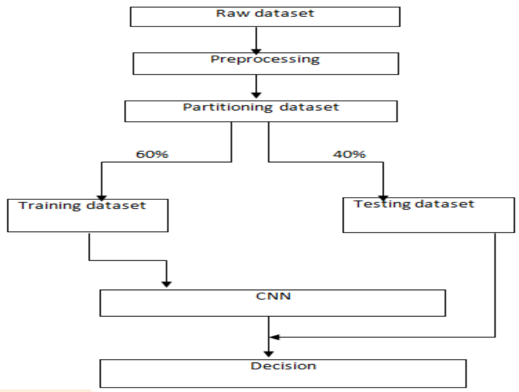

Fig.1.Block diagram of proposed method

3.1 Advantages

- Accurate classification
- Less complexity
- High performance
- Easy Identification

3.2 Drawbacks

- Less feature compatibility
- Low accuracy

IV.IMPLEMENTATION

- Firstly, we have collected the dataset of the Facial Cues images with the 2 classes (with the rug sick affected and rug healthy).
- Necessary pre-processing steps will be completed with the dataset before training with our algorithm.
- Once after training the model will be saved for testing and classifying.
- User can upload the images of which to be classified and by using the saved model the images will be classified and predicted.

V.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 followed by other convolution layers such as pooling layers, fully connected layers and normalization layers.

5.1 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 increasing depth. Reducing volume size is handled by max pooling. Two fully-connected layers, each with 4,096 nodes are then followed by a Softmax classifier. The "16" stand for the number of weight layers in the network. The VGG architecture is shown in below figure.

5.2 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.

5.3 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.

5.4 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 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.

5.5 Xception:

- Xception Model is proposed by Francois Chollet. Xception is 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.

- Xception models remain 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.

VI.UML DIAGRAMS

A use case diagram in the Unified Modeling Language (UML) is a type of behavioral diagram defined by and created from a Use-case analysis. Its purpose is to present a graphical overview of the functionality provided by a system in terms of actors, their goals (represented as use cases), and any dependencies between those use cases. The main purpose of a use case diagram is to show what system functions are performed for which actor. Roles of the actors in the system can be depicted.

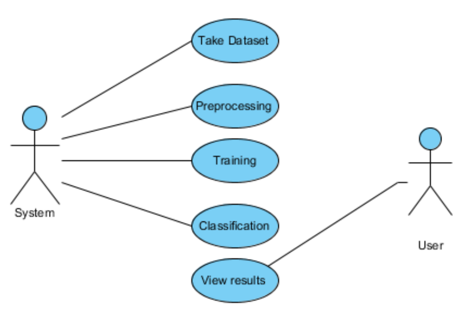

Fig.1. Use Case Diagram

VII Result and Discussion:

Tab.1 Partitioning Dataset Table

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

The Table 1 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).

Tab.2. Statistical data Analysis

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

Tab.3.Percentages of methods table

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

The Table 3 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 accuracy values will be shown in the table with model wise.

VIII OUTPUT SCREEN SHOTS WITH DESCRIPTION.

8.1 Home: In our project, we are classifying the presence of Facial cues illness or not, with the help of deep learning.

Fig.6.Home Screen Output

8.2 Classified output:

The uploaded image is classified as the person not affected with Facial Cue.

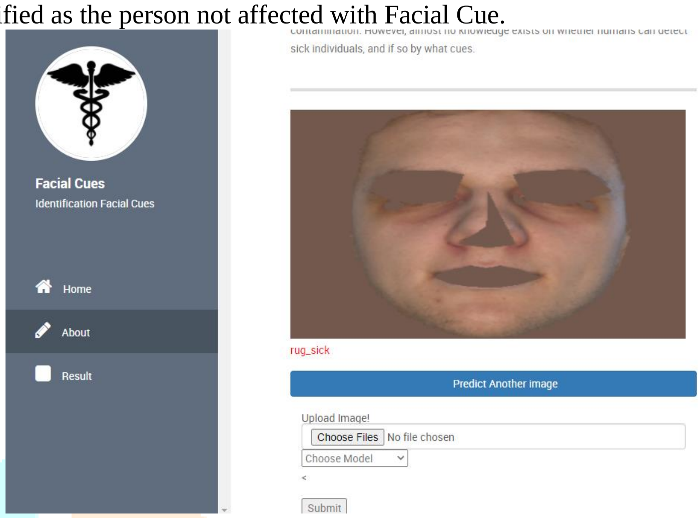

Fig7: Model choosing

8.3 Classified output:

The uploaded image is classified as person is normal i.e., affected with Facial Cue.

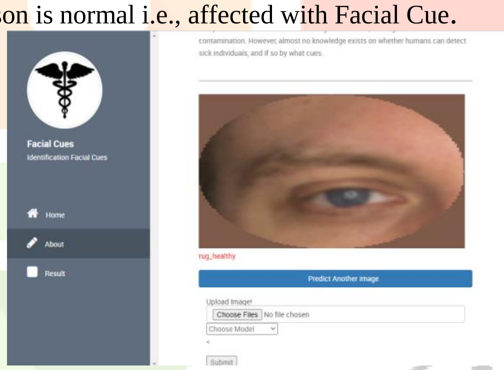

Fig.8.Classified output

IX.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.

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