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Facial Paralysis Severity Assessment via Convolutional Neural Network

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Abstract*— A scale to measure the nerve damage is necessary for automatic methods intended to evaluate the degree of facial palsy. The grading scales specifically divide the the facial nerve injury into a number of distinct stages in accordance with some stringent criteria. These measurements are related to auxiliary characteristics like synkinesis and deal with the symmetry of the face during neutral expressions or a sequence of voluntary facial movements. The facial palsy has various phases which include pre-processing, segmentation, feature extraction and classification. The voting classification model is proposed which is the combination of the multiple classifiers for the facial palsy prediction. The proposed model is implemented in python and results is analyzed in terms of accuracy, precision and recall.

***Keywords* — Facial Palsy, Feature Extraction, K-means, Severity, Voting Classifier.**

I. INTRODUCTION

When facial muscles on either side i.e left/right side or both sides are paralysed, it is referred to as facial palsy (FP) or face paralysis. Congenital defects, trauma-related nerve damage, or disorders like stroke, brain

tumours, or Bell's palsy can all cause this impairment. Patients having facial paralysis have trouble while speaking, blinking, ingesting saliva, eating, or expressing themselves naturally with their faces. This is because their facial muscles appear to be sagging. Most of the time, a clinician will just visually examine a patient's face symmetry to make a diagnosis. A diagnosis of facial palsy must be made after a thorough medical examination, and it may differ from practitioner to practitioner [1]. Recently, autonomous systems that incorporate artificial intelligence and computer vision have been developed in order to provide an objective assessment of the paralysis. According to their primary function, numerous approaches for treating facial palsy can be found in the literature. For instance, whether the goal is to do a multi-class classification or a binary classification to distinguish between normal and unwell patients [2] (i.e., to notice facial palsy or to evaluate the paralysis level).

To identify facial palsy, a number of automatic methods based on artificial intelligence and computer vision have been developed. Binary classification can be used for purposes other than identifying facial paralysis, such as determining the kind of facial palsy a patient has. A scale to compute the damage of nerve is important for automatic methods intended to assess the degree of facial paralysis. To start evaluating their algorithms, several authors divide the severity of facial palsy into smaller categories, such as healthy, mild, and severe degrees of paralysis and describe their findings [3].

1.1 Facial Palsy Severity Detection System

Rapid improvement and recovery are facilitated by a clear diagnosis and prompt treatment of FP. Majority of the accessible grading assessments are arbitrary, tedious, and are typically unused in everyday implementations [4]. For lower motor impairment, no standard clinical assessment is present yet. An accurate, unobtrusive, quantifiable, and objective facial paralysis evaluation and classification system is urgently needed [5].

Such a system is important for determining therapeutic decisions during rehabilitation and therapy and for monitoring progress during the follow-up phase. The illustration of the broad FP evaluation structure is shown in Figure 1.

Fig. 1: Facial Palsy Severity Classification

The right and left unilateral FP are both classified into three severity categories using the FP classification module that is described in this research. Along with the resting condition, this is done for many voluntary face movements. The processes of dataset construction, feature selection and extraction, and classification are covered in the following sections.

The classification module receives as inputs from the feature extraction unit depending upon the degree to which facial movements are performed symmetrically [6].

Data acquisition:

Multiple hospitals provide information regarding the severity classification of facial palsy. Patients with different levels of unilateral FP, primarily idiopathic, are included in this. Age group, sexual category, the paralyzed side, the severity, and ailment duration are other variables.

The patients are told to do a variety of voluntary facial gestures, including whistling, raising eyebrows, closing eyes, putting a smile on the face, and blowing cheeks. In addition to the resting condition, each of these motions is recorded with data [7]. To create the FP dataset, many samples of each movement were collected. Many examples of the same action were taken as samples from numerous patients.

Feature extraction & selection:

FACT (Facial Action Coding Technique) is a system for describing the motions of the facial muscles and how the face shape alters as a result. A variety of muscular motions, some of which can be performed by the same muscle, result in various variances in the facial expression. Each facial emotion is broken down into some action units (AUs) and these are the individual parts of the motions of the facial muscles. The two modules (symmetry or uniformity analysis module and facial functions grading module) are used as inputs to alter features using two different sets of facial animation units (FAUs). These attributes are then used to determine the animation symmetry indices using the symmetry analysis module (ASIs). The most impacted FAUs implicated in each of the various face movements are represented in the second set of features [8].

Classification:

The chosen FAUs are not utilized as direct inputs to the categorization module. The FAU's features are changed into new sets using two modules (symmetric and face functions grading module). There are commonly three classifications of unilateral FP - mild, moderate, and severe. The computations of FAUs are contrasted between the motions of the right hand side of face and left hand side of the face in the symmetry analysis module in order to calculate the ASIs of the three facial parts— oral region, eyes, and eyebrows [9].

The ASIs assessed while the person is grinning, for example, are supplied to the grinning classifier (the classifier that determines FP type and intensity relying on smiling activity) since the quantity of features from the symmetric module vary depending on different facial movements. The classifier compares computations of FAUs collected in time of each facial motion to their equivalent facial motions in the resting state to determine how successfully facial movement was executed. Therefore, these characteristics show how well each side of the face performs the facial movement [10].

II. LITERATURE SURVEY

G. S. Parra-Dominguez, et. al (2022) suggested a technique for analyzing and classifying the lesion severity as healthy, slight, and strong palsy [11]. The regional information was analysed. Four classification algorithms were implemented to accomplish multi-class classification to validate a set of presented manual attributes. The experimental outcomes indicated that the suggested technique offered an accuracy of 95.61% for detecting the palsy patients and 95.58% for evaluating the severity level.

A. Song, et. al (2018) presented a robust and precise computer method to classify FNP (Facial Nerve Paralysis) with the implementation of a single CNN (Convolutional Neural Network) [12].

The overfitting was avoided in effective manner using TL (transfer learning) for restricted range of images. The proposed method was compared with other techniques. The presented method yielded an accuracy of 97.5%.

S. Yaotome, et. al (2019) developed a facial palsy simulation technique in order to create the virtual facial images having similarity with the expressions of patients suffering from FP (facial palsy) [13]. CGAN (Conditional Generative Adversarial Network) algorithm was used for training a boundary-to-face network. This technique was capable of simulating the facial expressions of patients of facial palsy. The precise facial expression information was employed and the networks were enhanced to simulate any face.

Y. Xia, et. al (2022) projected a database known as AFLFP to classify the FP [14]. A Deep Neural Network (DNN) was presented for generating the outcomes with CFCN algorithm containing two stages for detecting the facial landmarks in facial palsy. The experimental results exhibited that the projected database illustrated the differences among them for detecting FP. Moreover, a facial landmark database was designed to detect and classify the facial palsy.

X. Liu, et. al (2020) introduced a hierarchical network with LSTM algorithm for enhancing the diagnostic accuracy and extracting FP detail from the shape of lower quality after outlining the sematic level features [15]. The facial region was segmented into two palsy areas for differentiating the FNP (Facial Nerve Paralysis) from normal face. YTFP and ECK Databases were employed to conduct the experiments. The experimental results depicted that the introduced network outperformed the existing techniques.

III. RESEARCH METHODOLOGY

The various steps for identifying facial paralysis at various stages are as follows:

Pre-processing:

This phase takes the images as the input. These images are gathered from reliable and publically available data source named Kaggle and inserted in a dataset. The input image is converted into gray scale to make further processing easy.

Segmentation:

This procedure is executed for dividing a digitized image into distinct portions. The different objects are recognized and the information is extracted from the image after segmenting the image. The image segmentation method is adopted for locating the required areas and bounding line of images. A label is allocated to each pixel. Various features are supported through each pixel that has same label. The images of leaves of plants are segmented on the basis of KMC (K-means clustering). This algorithm is useful to collect the samples into dissimilar clusters with regard to distance. The availability of two points closer to each other provides compact and independent cluster received as the closing target. The best value of K has been suggested as 3 for the FP images.

Feature Extraction:

The region of interest (RoI) is generated as an output from the segmentation phase. The goal of feature extraction phase is to determine the attributes from the required area. A set of values known as feature vector is thus created. Various components including colour, texture, morphology and color coherence vector are considered to detect the facial paralysis. These attributes are helpful in generating a disease detection model. GLCM technique is a statistical approach deployed for classifying the texture attributes.

Classification of Data:

Creating a classifier is the final step in the process of identifying FP. The entire dataset is divided into two parts – Training and testing. In comparison to the testing stage, more data is used during training.

This stage involves the use of KNN (K-Nearest Neighbor) method. For the purpose of demonstrating this classification algorithm, the unknown samples are related to the known ones separately or via similarity functions. The training and testing of this algorithm can be done at the same time. KNN can be used to find the K closest centres and assign the largest part's square to an unknown instance. The majority vote and its K neighbours are used to perform the classification. RF (Random Forest) is a powerful and flexible ML (machine learning) approach that incorporates a variety of tree predictors.

The outcomes of this algorithm are deemed to be ideal. The RF algorithm is capable of handling a large volume of data. The result from RF and KNN are deployed by the voting classification algorithm. This algorithm works well for selecting one of the two classifiers and determining the final prediction outcome. Fig 2 shows the scheme of classification.

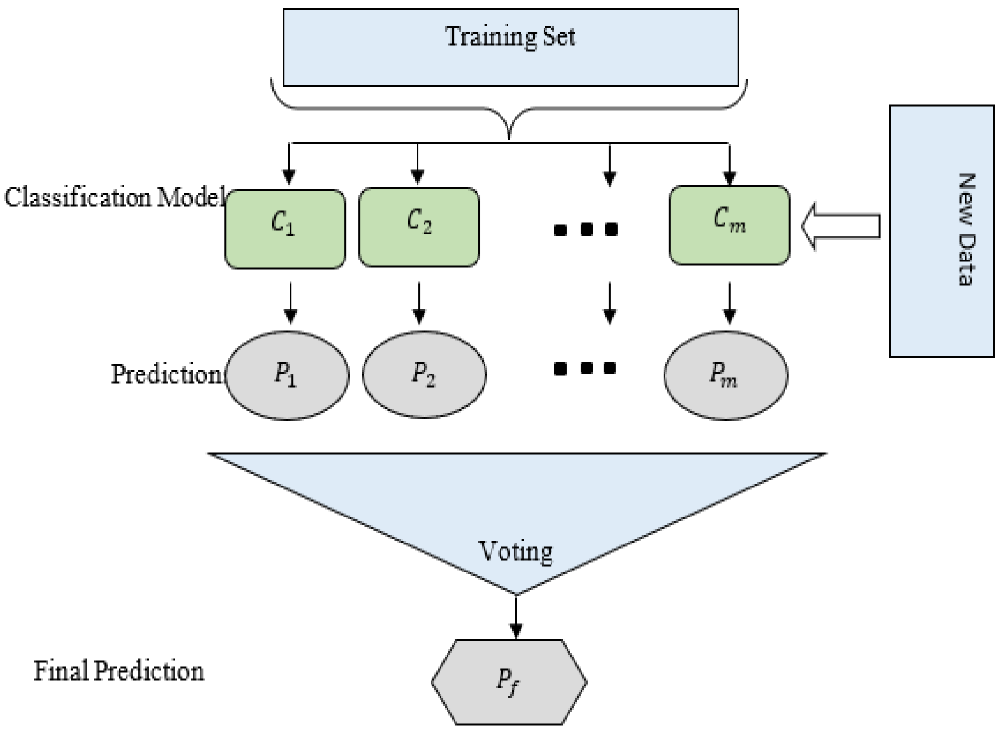

Fig. 2: Proposed Methodology

IV. RESULTS AND DISCUSSION

Python was used for the coding of various algorithm as it is self-explanatory, entity-driven, high-level dynamic programming language. It is frequently used as a scripting or glue language for connecting readily available components together as well as for rapid application development due to its high-level established data structures, dynamic typing, including binding. The readability of Python is enhanced by its straightforward syntax, which lowers the cost of software maintenance. Python provides modules and packages which improve the modularity and reuse of code in programs. The full-featured Python standard library is available in source or binary form for all popular operating systems free of cost. Applications supported by the Python API include GIMP, Inkscape, Blender, and Autodesk Maya.

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Fig. 3: Input Image

As shown in figure 3, the image from dataset is taken as input which is further processed for the facial paralysis detection.

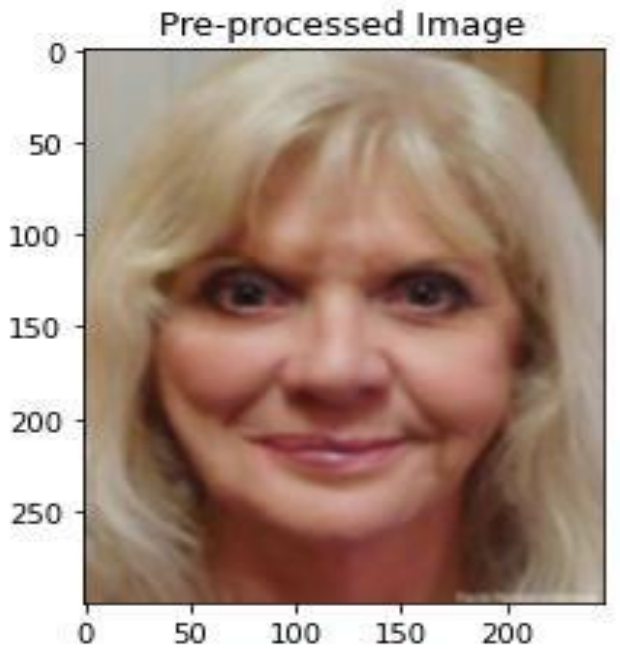

Fig. 4: Pre-Processed Image

As shown in figure 4, the image is pre-processed to remove noise and update size of the image. The Gaussian filter is applied which removes unwanted pixels from the image.

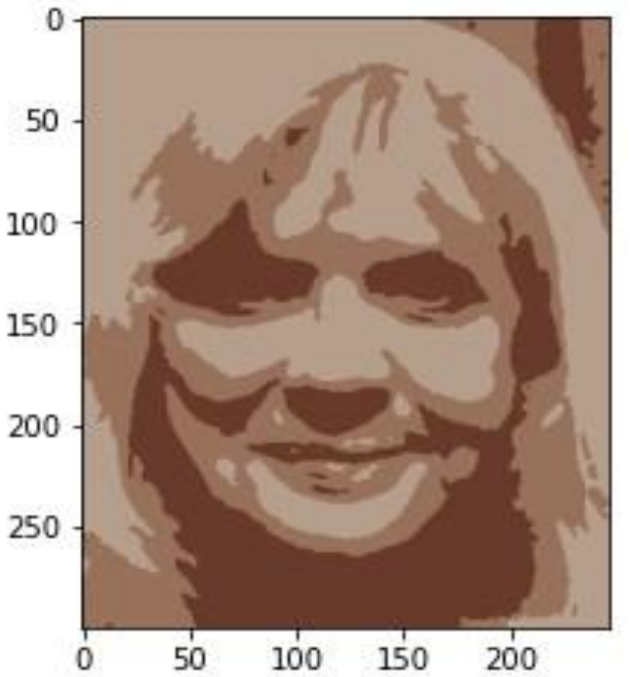

Fig. 5: Segmented Image

As shown in Fig. 5, the K-means segmentation is applied which helps to segment various portions of the image.

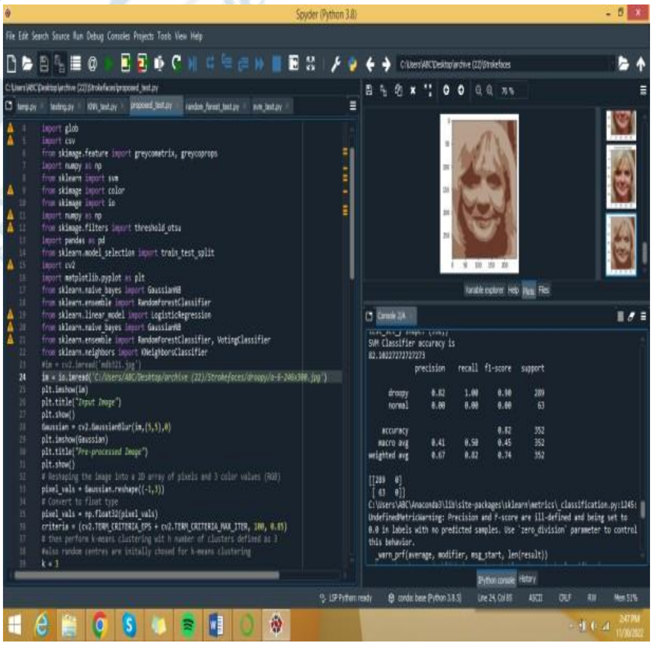

Fig. 6: Proposed Classifier

Fig. 6 depicts the proposed classifier applied for the facial paralysis prediction.

Table 1: Performance Analysis

Classifier	Accuracy	Precision	Recall
KNN Classifier	78.97	70	79
Random Forest Classifier	82.10	67	82
SVM Classifier	82.14	67	82
Proposed Classifier	92.5	93	93.2

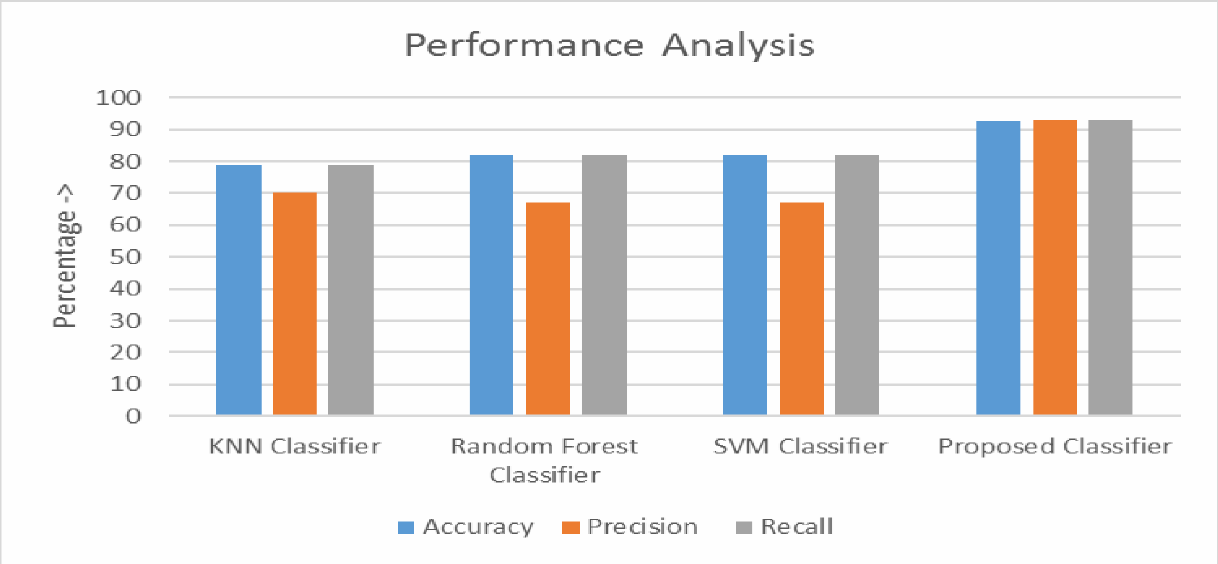

Fig. 7: Performance Analysis

Table 1 shows the comparison of proposed classifier with SVM, Random Forest and KNN classifiers for accuracy, precision and recall parameters. Fig. 7 depicts this comparison using bar chart. It was observed that proposed model gave higher accuracy, precision and recall than other existing classifiers.

V. CONCLUSION

To enable unbiased evaluation of the palsy, autonomous systems that integrate machine vision and machine learning have been developed. The various methods for the treatment of facial palsy can be classified depending on their principal function. To distinguish between healthy and unwell individuals, for instance, the objective can be to do a binary classification or a multi-class classification. For automatic procedures meant to assess the degree of facial paralysis, a scale to measure the neural damage is required. According to some strict criteria, the grading scales specifically classify facial nerve injuries into a number of separate stages. A novel model is proposed in this paper for the facial paralysis prediction. The proposed model is the combination of K-means for the segmentation, GLCM algorithm for the feature extraction and voting classifier for facial analysis prediction. The proposed model is implemented in python and result is analysed in terms of accuracy, precision and recall. It is observed that proposed model achieves a high accuracy of 93 percent for the facial paralysis prediction which is better than that obtained using any other classifier.

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