[1]Samuel Susan Veeravalli

Dr. Prajna Bodapati[2]

Evaluation of Asymmetry in Facial Palsy Images by Generating Facial Key Points and Contours

Journal of Electrical Systems

Abstract: - Facial Asymmetry is an effect of several diseases that are infected due to neural disorders. This has been growing rapidly among people of all age groups irrespective of earlier medical history and factors. The patients affected by this are unable to contract their facial nerve which results in droopy faces and deformation. Due to this many patients are also affected psychologically as this creates a phobia and discomfort for expressing themselves. As the facial expressions play a vital role for direct communication the social life of those people is been adverse. Recent study also shows that facial deformation is also an early sign of having strokes, so detecting any changes or deformation in facial features is desirable, which helps in detecting strokes beforehand. The advancement in technology helps in providing such a system for evaluating the facial images with computer vision methods. In this work, the facial images were analysed and key points of essential parts of face generated using the media pipe framework, which were considered for evaluating the asymmetry or droopy faces by comparison using Partial Curve Mapping (PCM) and other mathematical formulae. This assessment gives the level of asymmetry and can be further used for future diagnosis.

Keywords: Facial palsy, key points, Contours, Media pipe, PCM

Introduction:

Facial paralysis is a kind of illness that is seen normally with all age groups irrespective of previous medial history. This is not a widely spread disease but still its occurrence is increasing with a rapid growth of population, and is observed that about 30 persons out of 100,000 individuals [1] are affected by this. The other name for facial nerve paralysis is facial palsy, which is a disorder caused by a temporary or permanent facial nerve injury and thus the facial muscles cannot perform the contraction as normal.The facial muscles will be unable to communicate with the facial nerve resulting in a paralyzed portion of some part of the face. In some patients it will be difficult to show the expressions, movement of eyes, lips and also to convey some natural emotions during communication. This directly effects the social life of the patients infected with facial paralysis as they feel discomfort to communicate with others. There are also cases where patients are under severe mental depression due to the disfigured face and as they cannot go out in public like normal people. The paralysis on face is also affects at different degrees, it may on both sides of face or some particular portion of the face. If the cranial nerve is damaged on the side of a face, facial palsy is seen on that particular side of face, as the nerve cannot signal the muscles for normal functionality. The brain is the main source of a nerve, and it comes out and split into branches. The desired muscle for creating the facial expressions is provided by these branches, which are divided into five branches before the ears. Further they are also responsible for controlling other senses like taste, for generating saliva and tears.Facial Paralysis is the illness affected by many causes, like nerve injury or viral infections or strokes, in both adults and children at different level of intensity. One of the familiar forms of facial paralysis is idiopathic Bell’s Palsy [2], this is commonly seen in both adults and children, rating 54.9% and 66.2% respectively. Ramsay Hunt Syndrome [13][14] , is a viral infection which is another cause for the paralysis and has almost 26.8% in elders and 14.6 % in children. Another cause of paralysis which is concerned to be important is traumas like surgeries, stroke effects, accidents, child births are rated as 5.9% and 13.4 % in adults and children.

[1*]Dept. of Computer Science and Systems Engineering.Andhra University. Visakhapatnam,

India.vssusan.rs@andhrauniversity.edu.in

[2]Dept. of Computer Science and Systems Engineering. Andhra University.Visakhapatnam, India.

prof.bprajna@andhrauniveristy.edu.in

*Corresponding Author: Samuel Susan Veeravalli[1],

[*]Dept. of Computer Science and Systems Engineering.Andhra University. Visakhapatnam,

India.vssusan.rs@andhrauniversity.edu.in

Out of which 3.4% is due to birth of child, 2% is due to iatrogenic reasons, 1.8% of them is from adults infected with tumours, and the children with leukemia account up to 1.3%. The model based on CNN using autoencoders, given an input image with facial palsy is desired to be implemented to detect the intensity of asymmetry in the facial features. These kinds of models will be helpful for analysing the patient's condition and the recovery rate as the early diagnosis of such paralysis have a better chance of recovering.

Related Works

This study, by Kostiantyn Khabarlak et al. [5], provides a thorough summary of both conventional and deep learning-based methods for facial landmark identification. The authors compare each approach's performance on benchmark datasets and offer a thorough analysis of its advantages and disadvantages. The applications of facial landmark detection, such as face tracking, facial reenactment, and facial emotion identification, are covered in this work. Examples of these applications' use in a variety of industries, including security, healthcare, and entertainment, are given.

The study also outlines the drawbacks and restrictions of the available facial landmark identification techniques and makes recommendations for new lines of inquiry. Researchers who wish to address the current shortcomings of facial landmark identification techniques and create novel strategies to get around them will find this material to be extremely important.

esearchers wishing to grasp the state-of-the-art in facial landmark identification and pinpoint areas for further investigation can find several additional approaches [6] that have been proposed before for comparable results.Gemma S. Parra-Dominguez [7], for those researching the diagnosis and treatment of facial paralysis, in particular, this publication is extremely pertinent to the fields of medical imaging and computer vision. a thorough overview of the available approaches for identifying facial paralysis, such as image analysis, electromyography, and manual examination by medical experts. These approaches have limits, especially about availability, cost, and accuracy. Researchers who wish to comprehend the difficulties involved in detecting facial paralysis and the requirement for better techniques may find this material to be helpful. This suggests a novel approach to key point analysis-based facial paralysis identification. Use facial landmarks and key points to evaluate feature asymmetry and determine whether paralysis is present. Using a collection of face picture data, they assess the suggested method's performance and contrast it with other approaches.

According to Samuel Susan Veeravalli et al. [8], the recommended method categorizes the dataset of drooping face photos by contrasting it with the dataset of normal face photos. The best approaches for deep learning image classification enable the identification of faces in photographs that show signs of cerebral palsy. The trained models identify the same with a high degree of accuracy. Based on previous research and a comparison of the three models, DenseNet201 has the greatest accuracy for both training and validation. This makes it possible to identify those who have facial deformities using this approach.

Jiang Chaoqun, et al [9]. The publication offers a thorough examination of the current approaches for assessing facial paralysis, including image analysis, electromyography, and physical inspection by medical specialists. The authors draw attention to these techniques' shortcomings, especially concerning their expense, dependability, and accuracy. Researchers who seek to comprehend the difficulties involved in assessing facial paralysis and the need for better techniques will find this material to be very helpful. This classifies the degree of facial paralysis and identifies and quantifies face asymmetries using a mix of machine learning, feature extraction, and facial landmark recognition algorithms. Using a collection of face picture data, the authors assessed the suggested method's performance and compared it to other approaches that were already in use. The suggested method's possible uses in diagnosis, treatment planning, and rehabilitation are also covered in this study. The significance of promptly and precisely identifying facial paralysis and the possible effects of the suggested approach on the course of treatment.

An ensemble of regression tree-based facial feature extraction is the unique approach for effective facial paralysis classification proposed by Jocelyn Barbosa et al. in their study [10]. It is especially pertinent to researchers studying computer vision and medical imaging who are tackling the diagnosis and treatment of facial paralysis. The report offers a thorough overview of the current approaches for classifying facial paralysis, including image analysis, electromyography, and manual inspection by medical specialists. This suggests a novel approach to the categorization of facial paralysis, based on the extraction of facial features using an ensemble of regression trees. The authors categorize the degree of facial paralysis by extracting pertinent information from face photos using a mix of texture, symmetry, and landmark characteristics.

This research by Gee-Sern Jison Hsu et al. [11] offers a thorough overview of the many approaches currently used for the diagnosis of facial palsy, such as image processing techniques, electromyography, and physical inspection by medical specialists. The study suggests a novel hierarchical network-based technique for the diagnosis of facial palsy. The authors employ a convolutional neural network (CNN) to classify the degree of facial palsy after capturing local and global facial data using a multi-level feature extraction strategy. Using a collection of face picture data, they assess the suggested method's performance and contrast it with other approaches. The suggested approach works faster and more effectively than the state-of-the-art techniques while achieving high accuracy in the diagnosis of facial palsy. Researchers studying facial palsy diagnosis and therapy may find the paper to be a helpful resource. It may also stimulate fresh ideas for enhancing the precision and effectiveness of facial palsy detection.

An inventive telemedicine system called the Tele Stroke System (TSS) was created by Chandaliya et al. [12] to allow for the remote diagnosis and treatment of stroke patients. By connecting medical specialists with patients in remote areas through technology, the TSS system offers prompt and precise stroke diagnosis and treatment. To facilitate remote consultation, evaluation, and treatment planning, the TSS system offers several capabilities, including imaging tools, video conferencing, and connection with electronic health records. A secure platform for data exchange and communication between medical specialists is also included in the system, facilitating efficient teamwork in the treatment of stroke patients. According to one study by Nelson et al., stroke patients had better results because the TSS system made it possible for prompt and accurate stroke diagnosis and treatment. By facilitating access to stroke specialists and shortening treatment times, the TSS system was found to enhance stroke care in rural locations by Hess et al. [13] in another research. The TSS system's capacity to handle the difficulties associated with providing stroke treatment in underprivileged communities has also been acknowledged. The TSS system is one telemedicine system that can increase access to stroke care in rural and underserved locations, according to a review by Leira et al. [14].

Kim Jong-Wok et al. A computer vision job called "human pose estimation system" [15] includes locating and tracking key points or joints in photos or recordings of people. Applications for it include augmented reality, activity identification, human-computer interaction, and sports analysis. Real-time posture estimate is made possible by Google's well-known open-source MediaPipe posture package. This estimates the critical points on the human body using machine learning techniques, most especially deep learning models. Pre-trained models and a framework for incorporating pose estimation capability into applications are provided by the library to developers. When we discuss optimisation strategies concerning human posture estimation, we're talking about ways to hone and enhance pose estimation systems' precision. Typically, these techniques entail fine-tuning joint localization, changing model parameters, or adding more data to improve the estimation outcomes. There are other ways to optimise, including using biomechanical constraints, gradient-based optimisation, and expectation-maximization methods.

Methodology

In this work, the first interest is to find the key points and then use them for the evaluation of asymmetry level in faces for better analysis. Therefore, the following steps are involved for the same.

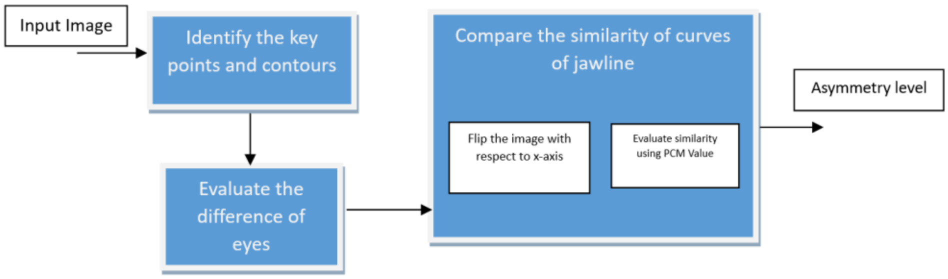


Fig 01: Steps in evaluation of asymmetry in facial images

I) Identifying the key points and contours

A framework or technology called MediaPipe is utilised to accomplish the goals in the context of contour identification and facial key points for the detection of facial paralysis. The "BlazeFace" model, which MediaPipe offers, is a pre-trained model for facial landmark identification. BlazeFace can precisely identify faces in picture or video frames and is made especially for real-time, on-device face identification. It gives the bounding box coordinates of every face that is found. After extracting face regions of interest using these bounding boxes, MediaPipe's "FaceMesh" pre-trained model is utilised to detect facial landmarks. This framework consists of the following steps shown in Fig 02.

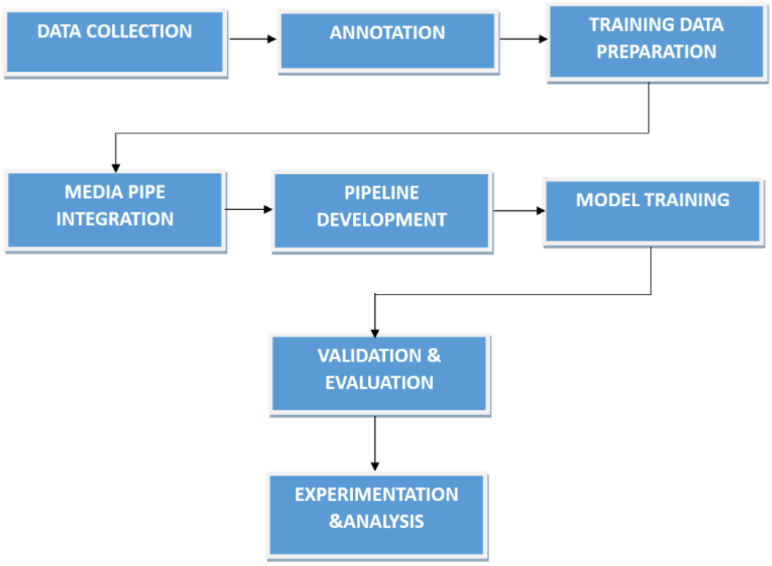


Fig 02: Steps in MediaPipe framework

A. Data Collection:

Firstly, a dataset of face photos or videos with a focus on people who have facial paralysis must be gathered. A wide range of patients with varied degrees of facial paralysis should preferably be included in the dataset, capturing a variety of face emotions and positions.

B. Annotation:

Key features and facial outlines must be marked on the gathered facial photos or videos through annotation. The term "key points" describes distinct features or points on the face, including the corners of the eyes, nose, lips, etc. The form or outline of several face features, including the lips, eyebrows, and jawline, is represented by contours. Depending on the resources available, annotation can be done manually or automatically.

C. Training Data Preparation:

There are training and testing subsets inside the annotated dataset. A machine learning model or algorithm is trained using the training subset to recognise and track face key features and contours. Pre-processing the data, which includes operations like resizing, normalisation, and augmentation, will improve the resilience and performance of the model..

D. MediaPipe Integration:

The research pipeline uses MediaPipe in order to take use of its contour and face key point detection capabilities. Calculators and particular MediaPipe parts needed for this activity are chosen and incorporated into the pipeline. Calculators for contour extraction, landmark recognition, and face detection may be among these components.

E. Pipeline Development:

The graph-based MediaPipe concept is used in the development of the pipeline. Based on their input and output streams, the chosen calculators are coupled to create a comprehensive data processing pipeline. Using the MediaPipe calculators, the pipeline should receive input facial photos or videos, conduct the appropriate processing processes, and output the contours and important points of the detected faces.

F. Model Training:

Using the annotated data, a machine learning model or algorithm is trained. This could entail methods such as deep learning, in which a neural network is trained to recognise and forecast face features and important points based on the input photographs. By integrating MediaPipe with well-known machine learning frameworks such as TensorFlow, researchers can train and implement their models directly within the MediaPipe pipeline.

G. Validation and Evaluation:

The testing subset of the annotated dataset is used to validate and assess the established workflow. The performance and accuracy of the contour identification and face key point are evaluated by contrasting the expected outcomes with the ground truth annotations. Measures of the pipeline's performance include accuracy, mean squared error (MSE), and intersection over union (IoU).

H. Experimentation and Analysis:

The created pipeline is used in studies or real-world situations including facial paralysis. A total of 468 key points from MediaPipe are used to create face mesh, out of which, 68 crucial key points are filtered as separate arrays for each facial component, such as the mouth, eye, and so forth. This might entail observing how the major features and contours of the face change over time, contrasting the characteristics of those who have facial paralysis with those who do not, or evaluating the efficacy of various therapies or treatments.

II Evaluate the difference between the eye

The key points generated from the previous step are analysed in this for evaluating the asymmetry level in faces. One potential difference that can be clearly observed in faces who are affected by the palsy is the difference among the eyes. As the patients are unable to contract the facial nerve, they will be finding it difficult to respond like others. Mostly the shape, size or angle of both eyes are not similar to each other. In this work, from the obtained key points of both the eyes, the difference between the area of right eye is compared with the left eye. This can be done by using the formula for given ‘n’ points

$$\text{Area} = \text{abs}\,\frac{(x1*y2 - x2*y1) + \cdots + (xn*y1 - x1*yn)}{2}$$

After computing the area of both the eyes the difference is calculated as

Diff=abs(Area_right_eye – Area_left_eye)

III Comparing the similarity on either side of face using jawline points

Another important feature that can be observed in the facial asymmetry is the difference of the shape with respect to the jawline. The other parameters are also essential like expressions and movement of lips while speaking which will not be normal compared to the healthy persons. The jawline analysis is useful even in cases without expressions or movements of facial muscles as it is clearly visible. Therefore, in this the curve that is generated with the jaw line is compared on either sides and checked for the similarity for both sides of face. PCM [18] is a method employed to assess the similarity or dissimilarity between hysteresis responses of materials. It involves mapping selected portions of one curve onto another, enabling a detailed comparison of cyclic behaviours. PCM is particularly valuable when analysing material responses to cyclic loading, such as stress-strain curves, magnetization curves, or any other cyclic phenomena encountered in material systems. The following steps are involved in this method

A. Selection of Curves: PCM begins with the identification of curves representing material responses under different conditions. These curves are typically obtained through experimental testing or computational simulations.

B. Partial Mapping: Rather than comparing entire curves, PCM focuses on mapping specific segments or intervals of one curve onto another. This partial mapping strategy allows for a more targeted analysis of similarities and differences between material responses.

C. Alignment and Comparison: The selected portions of the curves are aligned to establish correspondence between corresponding points. Various alignment techniques may be employed to ensure accurate mapping and comparison.

D. Distance Calculation: Following alignment, PCM utilizes distance metrics or similarity measures to quantify the degree of resemblance between the mapped segments. Common distance metrics include Euclidean distance, dynamic time warping (DTW), or other similarity measures tailored to the specific characteristics of material hysteresis responses.

Results

(a) (b) (c)

Fig 03: sample input and resultant key points and contours

The results for the methods that are discussed in this paper are given below. The first step of generating the key points for a sample image consisting of facial features with palsy are shown in Fig 03. This shows the input image, the 68 key points obtained and the contours of the respective input. The TABLE I, II depicts the values of the coordinates of the points, which are used in the next step for calculating the difference of area with respect to the key points of the eyes.

The area of the polygon formed by the left eye and right eye key points is 0.00045482and 0.000413141 respectively, the difference is obtained as 4.17E-5 which shows that left eye is almost 10% more compared to right eye. This is one parameter often observed in patients with palsy as the nerve weakens the movement of eyelids the eyes are exposed more than the normal level.

TABLE I: Key points for the Left eye in sample input 1

Left Eye	X axis Coordinate	Y axis Coordinate	Z axis Coordinate
Key_point_1	0.6283681392669678	0.3187626600265503	0.013253781013190746

Key_point_2	0.55450040102005	0.3251112103462219	0.004577903542667627
Key_point_3	0.6056909561157227	0.3278060555458069	0.0010177132207900286
Key_point_4	0.5780696868896484	0.3284919857978821	-0.0020491182804107666
Key_point_5	0.5834333896636963	0.308647553539276,	-0.005999237298965454
Key_point_6	0.6120883822441101	0.309451162815094	-0.0033134648110717535

TABLE II: Key points for the Right eye in sample input 1

Right Eye	X axis Coordinate	Y axis Coordinate	Z axis Coordinate
Key_point_1	0.39662909507751465	0.3235807418823242	0.028836777433753014
Key_point_2	0.46596312522888184	0.32703331112861633	0.01146114431321621
Key_point_3	0.41743186116218567	0.33093881607055664	.014010527171194553
Key_point_4	0.44371297955513	0.330994576215744	0.007747136987745762
Key_point_5	0.4382797181606293	0.31225255131721497	0.004022830631583929
Key_point_6	0.41081947088241577	0.31419336795806885	0.010185504332184792

In the step 3 of the method that is proposed the similarity between the left and right side of the face are compared using the PCM method. The jawline key points are depicted in the TABLE III, the difference in the curve length and the PCM value are very minor or equal to zero if both the curves are exactly same. For the given sample input the value of curve length difference cl=1.5017 and PCM= 5.034, which shows that there is a significant change of shape from one side to other side of the face.

Jawline	X axis Coordinate	Y axis Coordinate	Z axis Coordinate
Key_point_1	0.3597871661186218	0.4530295729637146	0.1619987040758133
Key_point_2	0.3467608392238617	0.3897527754306793	0.17955301702022552
Key_point_3	0.388702929019928	0.5009646415710449	0.1082213861751556]
Key_point_4	0.4754444658756256	0.5546146035194397	0.035481732338666916
Key_point_5	0.42802906036376953	0.5337013602256775	0.0673079565167427
Key_point_6	0.5109413266181946	0.557463526725769	0.02915825881063938
Key_point_7	0.3460754156112671	0.3058503270149231	0.13236115872859955
Key_point_8	0.37371718883514404	0.48005032539367676	0.13686534762382507
Key_point_9	0.345825731754303	0.3618828058242798	0.17616210877895355
Key_point_10	0.6796026229858398	0.4498734176158905	0.14129842817783356
Key_point_11	0.6941066980361938	0.385234534740448	0.1564493477344513
Key_point_12	0.6456747055053711	0.4992702007293701	0.09258896112442017
Key_point_13	0.5478217601776123	0.5544960498809814	0.03163151815533638
Key_point_14	0.6006574034690857	0.5331373810768127	0.057220686227083206
Key_point_15	0.691452145576477	0.3007637858390808	0.10905801504850388

Key_point_16	0.6634562611579895	0.4776039719581604	0.11814462393522263
Key_point_17	0.6952792406082153	0.3571077585220337	0.15245148539543152

Fig 03: sample input and resultant key points and contours

Fig: 4 Sample image without palsy and its respective key points and Contours

The resultant image shown in Fig 4 is the sample image with no deformation or asymmetry in facial features. The respective key points are obtained as shown in Fig 4(b) and contours in Fig 4(c). The coordinates for the key points are depicted in the TABLE IV, V for the eyes which are used in step 2 for calculating the difference in areas among the eyes.

TABLE IV: Key points for the Left eye in sample input 2

Left Eye	**X axis Coordinate**	**Y axis Coordinate**	**Z axis Coordinate**
Key_point_1	0.6493263840675354	0.41285064816474915	0.014572418294847012
Key_point_2	0.5860994458198547	0.4143419563770294	0.0012494762195274234
Key_point_3	0.6295356750488281	0.4198641777038574	0.002861304907128215
Key_point_4	0.6055338382720947	0.4190271496772766	-0.002149442210793495
Key_point_5	0.6114364266395569	0.402535080909729	-0.007585651706904173
Key_point_6	0.6354228258132935	0.4050423204898834	-0.0025959608610719442

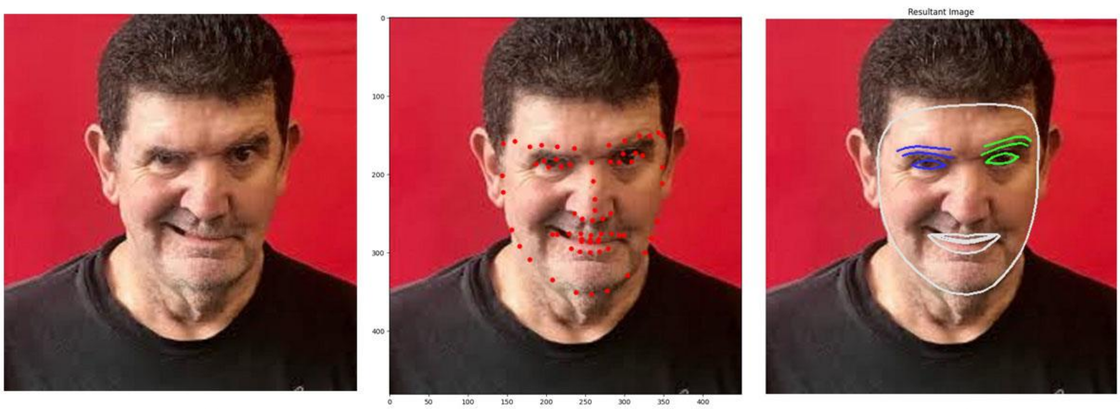
TABLE V: Key points for the Right Eye sample input 2

Right Eye	**X axis Coordinate**	**Y axis Coordinate**	**Z axis Coordinate**
Key_point_1	0.4417504370212555	0.4032628536224365	0.007835650816559792
Key_point_2	0.5056458711624146	0.41029295325279236,	-0.0016914823791012168
Key_point_3	0.4616430699825287	0.4116823673248291	-0.0026252460666000843
Key_point_4	0.4858161211013794	0.4129636883735657	-0.006228990387171507
Key_point_5	0.48186424374580383	0.3961772620677948	-0.011755717918276787
Key_point_6	0.45740944147109985	0.39653506875038147	-0.008214485831558704

As the input image is not having any signs of deformation the area for the eyes is obtained with not much difference. The area of the polygon formed by the left eye and right eye key points is 0.00030459 and 0.000318104 respectively, the difference is obtained as 1.35E -05 which shows that there is a negligible difference between the area which approximately 3%. This value can be considered as very low level of asymmetry as it is quite common in faces with minor differences. In order to get more precise value multiple images of the same person can be evaluated for a mean value of the difference to establish the correctness of the method.

TABLE VI: Key points for the Jawline in sample input 2

Jawline	X axis Coordinate	Y axis Coordinate	Z axis Coordinate
Key_point_1	0.38843315839767456	0.5535072684288025	0.14147435128688812
Key_point_2	0.3793935775756836	0.4782775938510895,	0.1481705904006958
Key_point_3	0.41785991191864014	0.6095306873321533	0.10067615658044815
Key_point_4	0.5030381083488464	0.6714403629302979	0.04404115304350853
Key_point_5	0.4582202732563019	0.6476837396621704,	0.06815064698457718
Key_point_6	0.5344502329826355	0.6750566959381104	0.0412166155874729l6
Key_point_7	0.38701552152633667	0.37734362483024597	0.09281551837921143
Key_point_8	0.4016331434249878	0.5852408409118652	0.12266980856657028
Key_point_9	0.380465567111969	0.44465404748916626	0.14048756659030914
Key_point_10	0.682318389415741	0.5619715452194214	0.15083466470241547
Key_point_11	0.6973568797111511	0.4888863265514374	0.1585894376039505
Key_point_12	0.6509984135627747	0.6152017712593079	0.10760750621557236
Key_point_13	0.5657537579536438	0.67266845703125	0.04598173126578331
Key_point_14	0.6104140877723694	0.6508731245994568	0.07265961170196533
Key_point_15	0.7010197639465332	0.3899085521697998	0.10332774370908737
Key_point_16	0.667484700679779	0.5923023819923401	0.13092012703418732
Key_point_17	0.6994490027427673	0.4560207426548004,	0.15135224163532257



(a) (b) (c)

The TABLE VI depicts the respective values of the coordinates for the jawline for the second sample image. As it is a normal face image, the similarity matching the is evaluated in the step 3 provides a very minor value as the difference when compared the either side of the face. For the given second sample input, after comparison the value of curve length difference cl= 0.73 and PCM= 1.90, which shows that there no significant change of shape or deformation is observed from one side to other side of the face.

Fig:05 Sample image from Kaggle dataset with droopy face and its respective key points and contours.

As a third sample input, an image from Kaggle dataset [16] is considered for analysis. In the Fig 05, the input image and the corresponding key point and contours are shown. The values of the key point coordinates are shown in TABLE VII, VIII which are necessary for the next step for evaluation. After calculating the difference in the area of left and right eyes using the second step of the method, the area of left and right eyes is obtained as 0.000576186 and 0.000541598. The difference between these is 3.46E -5, which is almost 7% more from one eye to the other.

TABLE VII: Key points for the Left Eye in sample input 3

Left Eye	X axis Coordinate	Y axis Coordinate	Z axis Coordinate
Key_point_1	0.7190458178520203	0.36721062660217285	0.010840545408427715
Key_point_2	0.6280308961868286	0.38354188203811646	-0.010846204124391079
Key_point_3	0.6885655522346497	0.3827832341194153	-0.004582847468554974
Key_point_4	0.6532004475593567	0.3848233222961426	-0.012946728616952896
Key_point_5	0.663214921951294	0.36221179366111755	-0.023046256974339485
Key_point_6	0.6992868185043335	0.36058926582336426	-0.014595655724406242

TABLE VIII: Key points for the Jawline in sample input 3

Right Eye	X axis Coordinate	Y axis Coordinate	Z axis Coordinate
Key_point_1	0.41635826230049133	0.38962888717651367	-0.012635797262191772
Key_point_2	0.5124590396881104	0.39268073439598083	-0.021364450454711914
Key_point_3	0.45170289278030396	0.3990997076034546	-0.02418881095945835
Key_point_4	0.48746544122695923	0.3967524468898773	-0.02792881801724434]
Key_point_5	0.4734358787536621	0.37757179141044617	-0.038395583629608154
Key_point_6	0.43796080350875854	0.38149362802505493	-0.034870490431785583

TABLE IX: Key points for the Jawline in sample input 3

Jawline	X axis Coordinate	Y axis Coordinate	Z axis Coordinate
Key_point_1	0.3467174768447876	0.5649627447128296	0.20266707241535187
Key_point_2	0.323994517326355	0.46546003222465515	0.19225342571735382
Key_point_3	0.39810213446617126	0.6438533067703247	0.15906114876270294
Key_point_4	0.5301477313041687	0.7316780090332031	0.09353644400835037
Key_point_5	0.4632391035556793	0.6984989643096924	0.12154792994260788
Key_point_6	0.5746347308158875	0.7342373728752136	0.09204863011837006
Key_point_7	0.32387322187423706	0.33614248037338257	0.09099569171667099
Key_point_8	0.3704410493373871	0.6087135076522827	0.18344447016716003
Key_point_9	0.32124724984169006	0.4207342863082886,	0.17267575860023499
Key_point_10	0.7587881684303284	0.5420559644699097	0.2333320677280426
Key_point_11	0.7734670042991638	0.442273885011673	0.22711136937141418

Key_point_12	0.725191593170166	0.6242092847824097	0.18301352858543396
Key_point_13	0.6184836030006409	0.7263413071632385	0.10030864924192429
Key_point_14	0.676128625869751	0.6854758858680725	0.13719487190246582
Key_point_15	0.7765175700187683	0.3145933151245117	0.1274280995130539
Key_point_16	0.7435541749000549	0.5871843099594116	0.21130633354187012
Key_point_17	0.7750087380409241	0.3983399271965027	0.20901061594486237

From the values of the jawline in TABLE IX, the curve similarity method is implemented and the value of the curve length difference is obtained as cl= 1.53 and the similarity index PCM= 3.59. As the input image is having the deformation on one side of the face, these values represent an evident difference when comparing both the sides.

As the results exhibit, with the sample images for evaluating the asymmetry level, images 1 and 3 are containing the faces with facial palsy or droopy faces, whereas image 2 contains the face without facial palsy. The values that are computed, prove to be reasonable for the methodology that is proposed. As the output values for image 2 are negligible compared to the vales of images 1 and 3.

Conclusion

In this paper, the necessity of identifying the key points and contour is elaborated. Media Pipe is the framework which is based on face mesh detection is used to obtain the points, out of the 68 key points that are generated some of them are used in this for evaluating the degree of asymmetry present in the facial features. The key points for both eyes are considered in the next step to compute the difference between the areas of then, as it is one key feature that can be easily observed in deformation of face. In the next step the Jawline curve is compared for similarity, from one side to the other. From the values that are calculated on the sample input images, clearly the difference is known for the images which have the palsy faces and which are almost symmetrical. Therefore, this study helps in evaluating the asymmetry of droopy faces. Furthermore, the key points that are generated can be used for comparing different other parameters like deformation of mouth, jawline difference on both sides from the centroid (nose centre), etc. This work facilitates to better understand the diagnosis or treatments that are available for facial palsy, when the images during the treatment phase are provided, the time for recovery can be analysed basing on type of disease, age, gender etc.

References

[1] GCha CI, Hong CK, Park MS, Yeo SG. Comparison of facial nerve paralysis in adults and children. Yonsei Med J. 2008 Oct 31;49(5):725-34. doi: 10.3349/ymj.2008.49.5.725. PMID: 18972592; PMCID: PMC2615370.

[2] Song, N. Y. Yen, J. Vong, J. Diederich, and P. Yellowlees, ''Profiling bell's palsy based on House-Brackmann score,'' J. Artif. Intell. Soft Comput. Res., vol. 3, no. 1, pp. 41–50, Dec. 2014.

[3] Sweeney CJ, Gilden DH, "Ramsay Hunt syndrome" Journal of Neurology, Neurosurgery & Psychiatry 2001;71:149-154.

[4] Kanerva, M., Jones, S. & Pitkaranta, A. "Ramsay Hunt syndrome: characteristics and patient self-assessed long-term facial palsy outcome". *Eur Arch Otorhinolaryngol* 277, 1235–1245 (2020). https://doi.org/10.1007/s00405-020-05817-y

[5] K. Khabarlak, L. Koriashkina Fast Facial Landmark Detection, and Applications: A Survey. Journal of Computer Science & Technology, vol. 22, no. 1, pp. 12–41, 2022.

[6] Y. Wu and Q. Ji, "Facial landmark detection: A literature survey," Int. J. Comput. Vision, vol. 127, no. 2, pp. 115–142, Feb. 2019, ISSN: 0920-5691. DOI: 10. 1007/s11263-018-1097-z.

[7] Parra-Dominguez GS, Sanchez-Yanez RE, Garcia-Capulin CH. Facial Paralysis Detection on Images Using Key Point Analysis. *Applied Sciences*. 2021; 11(5):2435. https://doi.org/10.3390/app11052435

[8] Samuel Susan Veeravalli, Dr. Prajna Bodapati. Deep Learning Approach To Detect Facial Asymmetry For Paralysis Detection. Journal of Theoretical and Applied Information Technology, 2023 June, Vol.101.No.12, E-ISSN:1817-3195

[9] Jiang C, Wu J, Zhong W, Wei M, Tong J, Yu H, Wang L. Automatic Facial Paralysis Assessment via Computational Image Analysis. J Healthc Eng. 2020 Feb 8; 2020:2398542. doi 10.1155/2020/2398542. PMID: 32089812; PMCID: PMC7031725

[10] Barbosa J, Seo WK, Kang J. paraFaceTest: an ensemble of regression tree-based facial features extraction for efficient facial paralysis classification. BMC Med Imaging. 2019 Apr 25;19(1):30. doi 10.1186/s12880-019-0330-8. PMID: 31023253; PMCID: PMC6485055.

[11] G. -S. J. Hsu, W. -F. Huang and J. -H. Kang, "Hierarchical Network for Facial Palsy Detection," *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, 2018, pp. 693-6936, doi: 10.1109/CVPRW.2018.00100.

[12] Chandaliya, Rishabh & Joshi, Praveen & Afli, Haithem. (2021). TeleStroke System (TSS) - Stroke Detection using Machine Learning.

[13] Hess DC, Audebert HJ. The history and future of telestroke. Nat Rev Neurol. 2013 Jun;9(6):340-50. doi: 10.1038/nrneurol.2013.86. Epub 2013 May 7. PMID: 23649102.

[14] Leira EC, Lamb DL, Nugent AS, Ahmed A, Grimsman KJ, Clarke WR, Adams HP Jr. Feasibility of acute clinical trials during aerial interhospital transfer. Stroke. 2006 Oct;37(10):2504-7. doi: 10.1161/01.STR.0000239661.07675.9d. Epub 2006 Aug 31. PMID: 16946166.

[15] Kim, J.-W.; Choi, J.-Y.; Ha, E.-J.; Choi, J.-H. Human Pose Estimation Using MediaPipe Pose and Optimization Method Based on a Humanoid Model. *Appl. Sci.* **2023**, *13*, 2700. https://doi.org/10.3390/app13042700.

[16] "Facial_Droop_and_Facial_Paralysis_image," Kaggle, 23-Aug-2019. [Online]. Available: https://www.kaggle.com/kaitavmehta/facial-droop-and-facial-paralysis-image. [Accessed: 20-Jan-2022]

[17] "Exact Algorithms for Partial Curve Matching via the Fr ́echet Distance" - Kevin Buchin†Maike Buchin†Yusu Wang- Proceedings of the 2009 Annual ACM-SIAM Symposium on Discrete Algorithms (SODA). 2009, 645-654 https://epubs.siam.org/doi/epdf/10.1137/1.9781611973068.71