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Advancements in Facial Paralysis Detection: A Review of Machine Learning and Deep Learning Approaches

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Abstract*: Facial paralysis drastically changes the lives of individuals and magnifies physicians' requirement for timely and accurate diagnosis and grading of facial paralysis for proper treatment and rehabilitation. Indeed, ordinary technologies such as manual examination and electromyography are very subjective, expensive, and too lengthy to detect facial paralysis. The notion of intelligent systems implementing ML and DL is a quantum leap in the field, enabling automation, precision, and scalability. This review article delves into the improvements in facial paralysis recognition and how the issues are solved through classical methods, mixed, and DL approaches. The study points out that the methods, the facial landmark analysis, the convolutional neural networks (CNNs), generative adversarial networks (GANs), and ensemble methods, which entail the implementation of different algorithms, have all have remarkable accuracy in the test, efficiency, and robustness. In addition, it has become possible to gauge real-time access to the diseased population by utilizing multimodal diagnostic systems, smartphones, and telemedicine applications. Despite these developments, issues like the limitations of data sets, lack of diversity, time restraints in real-time operations, and false model interpretations are still the real hindrances. The critique pinpoints the serious areas of study that already exist. It has a strong thesis on getting more prominent, still diverse datasets, using interpretable AI models, and seamlessly integrating into the clinical environment. Additionally, the writers urged the future search for more advanced features like the fusion technique and hybrid models that can be applied to detection and grading. This paper offers researchers and practitioners an extensive comprehension of the present approaches, challenges, and what lies ahead for future development, namely, the development of innovative and accessible intelligent systems for face paralysis recognition*

Keywords: Facial Paralysis Recognition, Deep Learning, Machine Learning, Facial Landmarks, Generative Adversarial Networks, Convolutional Neural Networks

I. INTRODUCTION

Facial paralysis, a medical term for loss, is the inability to move specific muscles of the face voluntarily and is often a cause for a visually noticeable sign of various facial expressions' asymmetry. The condition can result from several causes, such as neurological disorders, trauma, infections, or surgeries, and is often accompanied by medical issues like Bell's palsy, strokes, or facial nerve damage. The trustworthiness of face palsy identification and the investigation of its causes are the two prime areas of concern regarding its severity and developing the right strategy to deal with it. Early and accurate diagnosis can significantly improve rehabilitation results, avoid the development of long-term complications, and patients' quality of life is to be improved. The paralyzed face is typically diagnosed by conventional means such as doctors` visual examination, personal grading scales like the House-Brackmann (HB) system, and imaging techniques. Although these standard procedures are widely used, they are fundamentally subjective, time-consuming, and require the expertise of healthcare professionals. In addition, the assessments manually often suffer from inconsistent inter-observer variability, which leads to different results. These downsides show a need for automated systems that provide concrete, precise, and reliable evaluations.

In recent years, technology has advanced AI, ML, and DL in medical diagnostics beyond ever thought possible. Computational techniques let the scientists create systems that could learn and then identify facial paralysis, grade it, and answer the questions in the clinic. These processes acquire data from facial images, videos, and landmark points. They are used to detect facial asymmetries and quickly categorize the level of facial paralysis with very low error rates. Intelligent systems have proved to be very successful in the diagnosis of facial paralysis as a result of the integration of ML and DL algorithms. The new technologies enable complex data analysis like high-resolution facial images and videos to get the most important or valuable information. Issues like detecting the face's key feature, CNN, and GAN are Objectives of experimentally investigating techniques for solving one problem.

Facial landmark identification is a core step in various innovative systems that implies identifying the crucial spots on the face, like the eyes, nose, mouth, and jawline. These landmarks constitute reference points for predicting facial asymmetry and diagnosing deviations resulting from paralysis. To illustrate, the systems that use supervised descent methods or regression tree-based models have shown remarkable accuracy in detecting facial landmarks and classifying facial paralysis. Deep learning, especially CNNs, has intensively affected facial paralysis recognition by featuring the automatic seclusion of the features in images and videos. CNN-based models have been employed to analyze facial expressions, detect asymmetries, and classify the severity of paralysis with high accuracy. GANs, moreover, have been harnessed to produce synthetic datasets to be included in the training process, thus providing the system with more information about how to react to different situations and be more resilient to external changes.

The incorporation of multimodal data, along with facial photographs, videos, and medical statistics, has enhanced the overall performance and applicability of intelligent systems. Researchers have evolved hybrid models that integrate photograph-based total evaluation with real-time video processing and patient-specific clinical records by combining facts from several assets. Those methods allow a more excellent comprehensive assessment of facial paralysis, capturing each static and dynamic component of facial movements. For example, multimodal systems utilizing 3D imaging and point cloud evaluation have proven promise in capturing quality-grained info on facial asymmetry. Further, systems integrating smartphone-based applications and telemedicine structures have enabled real-time and remote diagnosis, especially in underserved areas.

Even though intelligent systems for facial paralysis recognition have made many improvements, some challenges and research gaps still need to be addressed. One of the key issues is the shortage of large, diverse, and standardized datasets for the training and validation of intelligent models. The current data sets have little variability in demographic diversity, lighting conditions, and facial expressions, leading to biases, and hence, the generalizability of the models is reduced. Another major problem is the need for explainability in AI models. Although deep learning models have been highly accurate, their black-box nature makes it difficult for clinicians to interpret and trust the outcomes. Developing explainable AI frameworks is significant for integrating technical developments with clinical usage. Real-time implementation is the other focal point that requires deeper consideration. Currently, most systems are too computationally intensive; thus, they may not be appropriate for deployment in areas with limited resources or on low-power devices (e.g., smartphones). Developing more computationally efficient and sensitive diagnostics is a central research area.

II. LITERATURE SURVEY

The literature on facial paralysis recognition spans traditional manual methods to advanced intelligent systems leveraging machine learning (ML) and deep learning (DL) techniques. This section categorizes and critically analyzes existing works to provide a comprehensive understanding of advancements, limitations, and trends in the field.

A. Traditional Diagnostic Methods

The classical techniques for the recognition of facial paralysis rely primarily on clinical assessments and subjective scoring systems like the House-Brackmann (HB) Scale and Sunnybrook Facial Grading System. These methods, despite being recognized, are subjective and have inter-observer variability. Techniques such as electromyography (EMG), MRI, and CT scans have been used to evaluate the functional status of facial nerves in greater detail. However, these are expensive and require specific equipment and know-how,further restricting their use.

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a. Manual Grading system

Manual grading systems have long been the cornerstone for evaluating facial paralysis in clinical settings due to their simplicity and ease of use. The House-Brackmann (HB) grading system, widely regarded as the gold standard, categorizes facial paralysis into six grades, ranging from Grade I, indicating normal function, to Grade VI, representing complete paralysis. This system provides a quick and standardized method for assessing the severity of facial nerve dysfunction. However, its reliance on subjective visual assessment often leads to inter-observer and intra-observer variability, which can affect the consistency and accuracy of evaluations. Studies, such as those by Evans et al. [1], have highlighted these limitations and underscored the need for more objective tools.Song et al. [2] utilized artificial intelligence to improve the reliability of the House-Brackmann scoring system used for assessing Bell's palsy. Although the model succeeded in increasing scoring precision, its failure to integrate with broader diagnostic frameworks remained a constraint.

Song et al. [3] enhanced the HB scoring system by implementing deep learning algorithms to achieve reproducible and accurate FP classifications. Still, it was not of much practical use because it could not be integrated into general diagnostic workflows. It concluded that AI might standardize FP grading, but further validation on large datasets should be done.Feng et al. [4] used EAR and blink rate as primary features in detecting facial paralysis. Based on the decision tree-based model, its accuracy was 85.7%. The effectiveness of eye movement features in early-stage detection was emphasized. However, the present method does not comprehensively evaluate facial paralysis because of the narrow focus on eye-based asymmetry.

The Sunnybrook Facial Grading System is the most widely used manual grading method, which aids a more comprehensive analysis because it addresses three independent parameters: resting symmetry, voluntary movements, and synkinesis (involuntary movements associated with facial activity). Although the Sunnybrook system offers a comprehensive view, it is very time-consuming and also very dependent upon the skills of the clinician to make it prone to subjectivity and inconsistency. Parra-Dominguez et al. [5] have pointed out that it helps assess improvement over rehabilitation but is tricky in application.

Despite manual grading systems like HB and Sunnybrook remaining in extensive use in clinical settings, their inherent subjectivity and imprecision limit the practicability and replicability. This reality encourages the use of automated, intelligent systems that should supply objective, reliable, and consistent evaluations to meet limitations that typical methodologies of manual grading systems have acknowledged.

b. Instrumental Grading system

Instrumental grading systems with specialized tools and technologies are aimed at achieving objective and measurable assessment of facial paralysis. Techniques such as Electromyography and 3D imaging systems have become widely used to evaluate the functional state of facial muscles and pathways. EMG measures the electrical activity of the facial muscles during voluntary or stimulated movements and helps ascertain the degree of damage to nerves and the prognosis. This method benefits rehabilitation planning by providingaccurate data to guide treatment decisions. However, EMG requires advanced equipment and trained personnel and cannot be accessible in resource-constrained settings. In addition, it can be invasive and uncomfortable for patients, making it less suitable for routine clinical use.

Advanced imaging modalities, such as 3D stereo photogrammetry and dynamic imaging systems, allow for the detailed visualization of facial symmetry and movement. For instance, Alagha et al. [6] used a 3D imaging system to grade the severity of facial paralysis objectively. Though these techniques are accurate, they are expensive and require highly specialized expertise, thus limiting their applicability to well-equipped health facilities. More importantly, their reliance on localized or concentrated parts of the face may limit their ability to evaluate such more widespread or complex cases of paralysis.Instrumental grading systems are substantially better than manual methods for grading because of increased objectivity and precision. However, the costs, technical sophistication, and inaccessibility to a broad audience call for more accessible and scalable systems, such as those delivered by machine learning and deep learning-based approaches. These will combine the precision of instrumental-based grading with the efficiency of automated systems to make the systems more clinically feasible.

B. Facial Landmark-based Methods

Facial landmark-based approaches form the essential aspect of the observation of facial paralysis. Identifying the key landmark points on the face, such as the eyes, nose, mouth, and jaw, is focused on determining these anatomic points, which allow symmetry assessment, detection of abnormalities, and classification regarding the degree of facial paralysis. The geometric relationships, asymmetry, and other discrepancies between these landmarks provide insight into the facial nerve's severity and kind of impairment.

KostiantynKhabarlak and colleagues [7] present an extensive overview of traditional methodologies and deep-learning approaches for identifying facial landmarks. The authors conduct a comparative evaluation of the performance of each method on standardized datasets and provide a comprehensive examination of their strengths and weaknesses. This study also discusses various applications associated with facial landmark detection, including face tracking, facial reenactment, and the recognition of facial emotions. The use of these tools in various sectors, including security, healthcare, and entertainment, is illustrated with examples.

Gemma S. Parra-Dominguez [5] claims that this paper is highly relevant to those involved in the study of the diagnosis and treatment of facial paralysis, especially in medical imaging and computer vision. It offers an overview of the methods available for facial paralysis detection: image analysis, electromyography, and doctor-based measurements. However, these methods have limitations related to their accessibility, cost, and accuracy. This information might be helpful to scholars who intend to know the challenges of identification in facial paralysis and the necessity for better methodologies. It, therefore, implies an innovative approach to identifying facial paralysis based on key point analysis. The use of facial landmarks and key points makes one assess feature asymmetry and establish the presence of paralysis. They use a dataset of facial pictures to evaluate the proposed method's effectiveness and compare it against other methods.

Jiang Chaoqun and colleagues [8] have provided an in-depth review of current techniques used to assess facial paralysis, which include imaging analysis, electromyography, and clinical examinations by medical personnel. The authors point out the shortcomings of these methods, especially concerning their price, reliability, and accuracy. The investigators seeking to know what challenges lie with assessing facial paralysis, including the need for better techniques, will find this information very helpful. It is this categorization that clarifies the severity of facial paralysis and identifies and quantifies facial asymmetry through the application of machine learning, feature extraction, and algorithms for facial landmark detection. Utilizing a dataset comprising facial images, the authors evaluated the efficacy of the proposed methodology and juxtaposed it with existing techniques. This research also addresses the potential applications of the proposed method in the realms of diagnosis, treatment formulation, and rehabilitation. The importance of swiftly and accurately diagnosing facial paralysis and the prospective implications of the proposed approach on treatment trajectories is underscored.

The novel approach for the classification of effective facial paralysis by Jocelyn Barbosa et al. [9] in their recent study is the ensemble of regression tree-based facial feature extraction. This is highly specific to researchers working on computer vision and medical imaging to address the diagnosis and treatment of facial paralysis. The paper discusses an overall scrutiny of the current methodologies adopted in the classification of facial paralysis, ranging from image analysis, electromyography, and even manual assessment performed by physicians. Therefore, this points out a different approach to classifying facial paralysis based on features derived from the face using regression trees. They classify the severity level of facial paralysis based on relevant data obtained from face images using a combination of texture, symmetry features, and landmarks.

A comprehensive review of FP Gaber et al. [10] used FAUs for quantitative grading and classification. This research used the Kinect v2 sensor with SDK 2.0 to obtain FAUs and facial landmarks from a dataset of 375 records from 13 patients. The three modules were symmetry analysis, evaluation of facial function performance, and grading of facial movements. The results proved that the system was non-invasive, objective, and efficient. Nevertheless, diversity in FP severity levels and larger datasets would enhance the validation and applicability of such studies.

Arora et al. [11] propose a multi-model framework for early detection of facial palsy in video streams using convolutional neural networks (CNNs). The framework combines a multi-task cascaded convolutional network (MTCNN) for face and landmark detection with a second CNN for palsy classification and obtains high accuracy on video data. The method and its data augmentation strategies deliver a training accuracy of 97% and a validation

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accuracy of 95%. However, the study emphasizes larger datasets and better management of complex facial expressions to enhance the robustness.

Afifi et al. [12] performed landmark-based facial paralysis detection methods with geometric relationships among points in the face using their respective SVM classifier. Their main demonstration was that the Landmark-based methods were more intuitive and computationally efficient, even allowing a 70% accuracy; in practice, however, reliance on such methods on hand anno- tated facial features made them vulnerable to random and distortion noise in images.

Gogu and Sathe [13] proposed an ensemble stacking model that integrated multiple feature extraction techniques, including FAUs, landmarks, and eye-based features. Their approach achieved a detection accuracy of 97.7% and a grading accuracy of 88.2%, demonstrating multimodal feature fusion's robustness. However, computational efficiency and model complexity were still challenging to balance.

Y. Xia et al. 2022 introduced a database termed AFLFP for the classification of facial palsy (FP) [14]. A Deep Neural Network (DNN) was developed to present results using a CFCN algorithm that was divided into two stages that could detect facial landmarks relevant to facial palsy. Results from the experimentation proved that the developed database appropriately showcased the differences related to the detection of FP. Moreover, a landmark database for the face was created to enhance the detection and classification of facial palsy.

C. Machine Learning-Based Methods

Machine learning-based methods became feasible tools to automatically detect facial paralysis by evaluating facial characteristic patterns for objective and reliable assessment. Generally, such approaches depend on manually developed features, including facial landmarks, symmetry indexes, and texture descriptors from face images, followed by evaluation against algorithms like Support Vector Machine (SVMs), RFs, and k-NN.

a. Feature-Based Approach

Feature-based methods in machine learning depend on extracting manually crafted features from facial images, which may be in the form of symmetry indices, texture descriptors, or geometric relationships among facial landmarks. The features are then used in machine learning algorithms like SVMs, RFs, or k-NN to classify or evaluate facial paralysis.

Barbosa et al. [15] proposed the system paraFaceTest based upon an ensemble regression tree for facial feature extraction that classifies facial paralysis. It used a dataset of 440 facial images by integrating a Histogram of Oriented Gradients (HOG) with a linear classifier. Their approach was found robust by having 97.48% sensitivity and a specificity of 94.91%, but with negative points, privacy-related restrictions within the dataset, and difficulties in applying generalization to broader populations.

Jiang Chaoqun and colleagues [8] present an extensive analysis of contemporary methods utilized in evaluating facial paralysis, encompassing image analysis, electromyography, and physical examinations conducted by healthcare professionals. The authors highlight the limitations associated with these techniques, particularly their costs, reliability, and precision. Investigators interested in understanding how to address the difficulties posed by facial paralysis assessment or the need for better methodologies will see this information particularly helpful. This approach classifies the degree of facial paralysis while detecting and measuring facial asymmetries by incorporating machine learning, feature extraction, and algorithms for facial landmark recognition. Using a dataset of facial images, the results of the proposed methodology are tested based on its effectiveness and compared with the existing techniques to validate its effectiveness. This study has also explored possible applications of the proposed algorithm in diagnosis, treatment planning, and rehabilitative care, besides underlining the need for speedy and accurate diagnosis of facial paralysis and possible implications on the therapeutic prognosis. Kim Jong-Wok and colleagues [16] define a computer vision task as a "human pose estimation system," which involves identifying and monitoring key points or joints in images or videos featuring individuals.

These potential applications range from augmented reality and activity recognition to human-computer interaction, all the way to sports performance analysis. Google's widely known open-source MediaPipe posture package facilitates real-time posture estimation. This is possible by applying machine learning methodologies, including deep learning models, to determine the human body's key points. The library offers pre-trained models and a framework designed to embed pose estimation functionality within an application. Optimization strategies concerning human posture estimation mean optimizing or honing pose estimation systems in precision. Typically, the techniques involve fine-tuning joint localization, changing model parameters, or adding more data to improve the results. Biomechanical constraints, gradient-based optimization, and methods based on expectation maximization also contribute to optimization. Guarin and Dusseldorp [17] introduced a machine-learning system for the automated localization of facial key points and symmetry evaluation. The system used 2D facial images to measure symmetry. Although effective for normal subjects, the system struggled with significant facial asymmetries in FP patients, mainly due to image resolution sensitivity and variations in head poses.

Kim et al. [18] developed a smartphone-based automatic diagnosis system for facial nerve palsy. The system used facial image capture and machine learning models to classify paralysis severity. It had real-time diagnostic capabilities but struggled to handle diverse lighting conditions and facial accessories like glasses or mustaches.Chong et al. [19] validated the Auto-eFACE, an automated facial palsy assessment tool integrating machine learning with the eFACE scale for facial symmetry analysis. The tool agreed well with clinician-graded assessments but needed further refinement to be accurate in severe FP cases.

Kim et al. [20] developed a smartphone-based system for diagnosing facial palsy using machine learning. It showed high accuracy but failed with lighting and environmental conditions variations, focusing on robust preprocessing.Chiesa-Estomba et al. [21] The strategy followed was applying K-nearest neighbor (KNN) algorithms that predict FP in patients having parotid gland surgery. The method applied to a set of 356 patients had more than 90% specificity. However, the event rate was low, limiting its applicability in other FP cases, thus bringing down its clinical value.Alagha et al. [6] presented a dynamic 3D stereo photogrammetry system for grading FP severity. The method was tested on 16 patients and achieved 73.2% and 91.1% accuracy. Although accurate, this method was limited because it relied on the central facial region for analysis; it was not very useful for detecting more diffuse FP cases.

Feature-based approaches have several benefits: they are easy, efficient, and effective as they require comparatively fewer computational resources. Deep learning architectures come second to feature-based strategies since they are more interpretable. However, these strategies present limitations: their design depends on manual feature engineering. Manual feature engineering is so time-consuming and even produces a potential bias. Besides these challenges, they fail to offer good results when variations in conditions like lighting, pose, and facial expression arise.

b. Regression-Based Models

Regression-based models are primarily used to predict continuous metrics that reflect the severity of facial paralysis. These models assess asymmetry and functional deficits based on characteristics obtained from facial images.

An ensemble of regression tree-based facial feature extraction is the novel approach for effective facial paralysis classification proposed by Jocelyn Barbosa et al. in their study [9]. It is especially relevant to researchers studying computer vision and medical imaging who are fighting the diagnosis and treatment of facial paralysis. The report contains an all-inclusive description of the techniques prevailing to classify facial paralysis, such as picture analysis, electromyography, and examination carried out by health professionals. This means adopting an innovative technique forclassifying facial paralysis based on regression trees that obtain facial features. Authors classify the severity of facial paralysis after processing relevant data from facial photographs using a combination of texture, symmetry, and landmark features.

Xiong and De la Torre [22] presented supervised descent methods to address face alignment challenges. Their regression-oriented technique facilitated accurate alignment of facial characteristics, demonstrating robust effectiveness in controlled environments. Nevertheless, the research recognized considerable demands on computational resources as a constraint, highlighting the need for additional optimization to enhance practicality in real-world applications.Raj et al. [23] used deep feature regression for objectively grading facial palsy indices. They applied pre-trained CNNs to extract the deep features and individual linear regressors to train different eFace sub-scores. This method proved significantly accurate in facial grading but had problems with subjective data annotations and no dynamic evaluation.

Gaber et al. [24] presented a classification framework that relies on facial animation units (FAUs) extracted from Kinect V2 sensors. In this study, the severity of FP was classified into seven categories using ensemble-based ML techniques, stacking, and bagging. The ensemble classifier proved robust and more generalizable, with an accuracy of

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96.8% on imbalanced datasets. However, the challenges were few, such as low diversity in datasets and missing some severity classes, sofurther exploration was needed.

Barbosa et al. [15] introduced paraFaceTest-a, a data-driven system based on an ensemble of regression trees, which is particularly apt for extracting facial features for facial paralysis classification. This technique was based on a dataset of 440 images and included HOG features with a linear classifier. Their approach provided a sensitivity of 97.48% and specificity of 94.91%, which meant its aptness for asymmetry detection, but privacy and access to the dataset were issues, along with less generalizability.

The principal benefit of regression-based models lies in their ability to provide thorough, quantitative assessments rather than just simple categorical classifications. This is particularly useful for tracking rehabilitation progress or assessing the impact of treatments. However, these models are sensitive to the quality and variation of input features, which makes them prone to overfitting when faced with minor or noisy data. They also require well-prepared datasets and careful feature selection to ensure accurate and statistically significant predictions.

Feature-based and regression-based methodologies have improvedmachine-learning applications for facial paralysis recognition. However, these inherent limitations necessitate the development of hybrid models and deep learning strategies capable of automating feature extraction and enhancing robustness in various contexts.

D. Deep Learning-Based Methods

The methods of grounding are now fundamentally changing the recognition of facial paralysis by automating procedures for the extraction of feature processes that have been allowing for highly accurate and scalable solutions. These methodologies base complex architectures such as CNN and LSTM networks that take care of facial images and video analyses, identify asymmetry, and determine the amount of paralysis. By directly analyzing unprocessed data, deep learning models eliminate the need for manual feature engineering, a strong constraint associated with conventional machine learning techniques.

a. Convolutional Neural Networks (CNNs)

CNNs are a cornerstone of deep learning-based approaches that can analyze image data and extract hierarchical features. Networks like this have been widely used for facial paralysis classification, and many results show state-of-the-art performance in those studies.

In their approach, Samuel Susan Veeravalli et al. [25] proposed a drooping face image dataset classification methodology comparing the same with a standard face image dataset. Deep learning image classification strategies effectively aid in the facial identification of images that characterize cerebral palsy. The trained models are observed to be quite precise during these identification processes. Based on reports from previous studies and comparing these models, DenseNet201 indicates maximum training and validation accuracy. Therefore, with this method, it is possible to detect those with facial defects. A comprehensive review of the different approaches currently used in diagnosing facial palsy has been undertaken by Gee-Sern Jason Hsu and other researchers [26], including image processing techniques, electromyography, and physical assessments carried out by healthcare professionals.

This paper offers a novel network-based, hierarchical approach for detecting facial palsy. The authors adopted a CNN to classify different levels of facial palsy with the help of multilevel feature extraction based on acquiring both local and global information regarding faces. They chose a facial image dataset and compared it with other techniques concerning its accomplishment. The proposed methodology works faster and more efficiently than modern techniques while accurately diagnosing facial palsy. Researchers diagnosing and treating facial palsy can consider this paper a helpful reference. In addition, it can also inspire new ideas that are aimed at enhancing the precision and efficiency of facial palsy identification. Song et al. [27] proposed a deep neural network-based approach for classifying facial nerve paralysis. Deep learning models were trained on clinical datasets based on the neurologist-standard classification system. The proposed approach was promising in terms of accuracy in classifying the severity of facial paralysis but had limitations with limited diversity in datasets and integration into real-time systems. Sajid et al. [28] have compared handcrafted and deep learning-based techniques for facial palsy classification. They used a CNN with GAN-based augmentation to enhance the model's performance and obtained 93% accuracy using VGG-16. The authors proved that

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deep learning outperforms traditional machine learning models like SVM and LDA but also emphasized the need for advanced augmentation for better generalization.

b. Advanced Deep Learning Models

Even though CNN forms the basis of most systems, other deeper architectures like LSTMs and hybrid have been developed to tackle other complex issues in facial paralysis recognition, such as temporal dynamics and detailed feature generation.Samuel Susan Veeravalli et al. [29] recommend that the proposed methodology groups the face image dataset drooping by comparing the dataset with the standard face image dataset.The best approaches for deep learning-based image classification allow the identification of facial features in images with symptoms of cerebral palsy.

The trained models exhibit a high degree of accuracy in their identification. From the previous studies and analysis of the three models, it can be derived that DenseNet201 has achieved the highest accuracy during both the training and validation phases. Hence, this methodological approach is feasible to identify people with facial deformities. A "human pose estimation system" is defined by Kim Jong-Wok et al. [16] as finding and tracking important points or joints in images or videos of people. Applications include augmented reality, activity recognition, human-computer interaction, and sports analysis.

This open-source posture package by Google is famous for its ability to estimate real-time posture. The package uses machine learning methodologies, especially deep learning models, to estimate key points in the human anatomy. Also, the library offers pre-trained models and a framework to allow developers to integrate pose estimation functionalities into their applications. Other pertinent methods used in optimization techniques for human posture estimation are methodologies toward refining and improving the accuracy of the pose estimation system. Such approaches are usually used to adjust joint localizations, change model parameters, or add extra data for improved estimation performance. The other optimization alternatives would also involve biomechanical constraints, gradient optimization techniques, and expectation maximization. Cootes et al. [30] have introduced the Active Appearance Model (AAM) that aims at facial feature extraction. Their method integrated statistical representations of facial geometry and appearance to discern essential facial characteristics. Although the method is valid in controlled conditions, it showed considerable variability in naturalistic environments, which requires more adaptive modeling techniques.

Szegedy et al. [31] proposed the deep convolutional network architecture: GoogleNet. It contains inception modules, which allow effective multiple-scale feature extraction. The improvement was seen in terms of accuracy improvements regarding face recognition tasks. However, changes to the model to take in very dynamic facial expressions continue to be challenging and require further improvement.Howard et al. [32] designed MobileNetV3, especially for mobile and embedded systems. They focused on a lean neural network, which uses minimal computations. The authors presented promising results in mobile implementations, particularly with resource-scarce systems. The paper, however, recommended its usage as part of the broader AI system.

Amsalam et al. [33] have done comparative studies of pre-trained deep learning models, such as ResNet, DenseNet, and VGG16, for real-time facial palsy detection. The best accuracy achieved by DenseNet was 98%. However, generalizing the results to multiple datasets and demographic differences posed a challenge.Boochoon et al. [34] presented deep learning-based applications of facial nerve palsy assessment and focused on extraction, accuracy of classification, and explainability. However, it came out that with such outcomes, explainability and the transparency of deep learning models turned out to be significant challenges wherein an explainable AI framework was required.

Goodfellow et al. [35] applied generative adversarial networks (GANs) to generate synthetic data for facial palsy classification, enhancing training dataset diversity and model generalization. However, real-world validation revealed limitations in the authenticity of GAN-generated data, suggesting the need for improved generation techniques.Ge et al. [36] proposed the Adaptive Local-Global Relational Network (ALGRNet) to predict the degree of facial paralysis using facial action units (FAUs). This model obtained an accuracy of 75.4% on the FPara dataset, which showed that FAUs play a critical role in identifying slight muscle movements. However, this method suffers from the problems of dataset bias and requires large amounts of annotated data for better generalization.

Liu et al. [37] proposed a hierarchical network combining CNNs with LSTMs to evaluate facial paralysis. This network segmented the facial region into affected and unaffected areas, extracting semantic-level features for detailed analysis. Including LSTMs allowed the model to capture temporal dependencies in facial movements, improving the evaluation

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of dynamic expressions. This approach demonstrated superior performance on benchmark datasets, highlighting its capability to differentiate between normal and paralyzed faces.Yaotome et al. [38] designed a conditional generative adversarial network for facial palsy expression, and their proposed CGAN-based framework generated synthetic facial images from the model. These images depicted expressions in patients who have facial paralysis that would help train and test the efficacy of the model. Another key point is that CGANs eliminated the need for a limited amount of labeled data and presented one more view to mimic disease-specific representations.

Rodríguez Martínez et al. [39] proposed "DeepSmile," an anomaly detection system for evaluating smiles in patients with facial paralysis. The system used LSTM networks to analyze facial movement temporal sequences, thereby detecting anomalies in normal expressions. The GUI was designed for clinical use, and DeepSmile achieved high precision in distinguishing pathological smiles from healthy ones. However, its reliance on limited and homogeneous datasets limited its ability to generalize across diverse populations and cases.

Deep learning methods have gone from CNNs and more advanced structures to LSTMs and GANs with facial paralysis recognition. CNNs can be very effective and accurate in image classification and recognizing asymmetry and grading degrees. More advanced models that will add the power of LSTMs and GANs will address more complex questions: temporal dynamics and how little data is available. Despite the significant success that these approaches have gained, there are still issues related to the heterogeneity of datasets, computational cost, and clinical workflow integration. Future research should concentrate on more interpretable models, generalization to other populations, and improvement in real-time applications.

E. Multimodal and Hybrid Systems

Multimodal and hybrid systems have become advanced approaches in facial paralysis recognition, using multiple data sources or combining different methodologies to increase precision, robustness, and applicability. These systems overcome the challenges of single-modal approaches by combining information from different types, including images, video sequences, and 3D data, to provide a more extensive view. Besides, they improve the capability of facial paralysis recognition systems by integrating real-time and telemedicine applications to make them useful in clinical and remote locations.

a. Integration of Multiple Data Types

Sforza et al. [40] proposed a three-dimensional superimposition method for assessing facial symmetry in patients with FP. Using stereophotogrammetry, the study produced 3D scans of the faces of the patients and computed symmetry indices using a specific software package. Although the method offered detailed assessments, it was expensive and involved specialized clinicians, hence making it less accessible to be applied broadly in a clinical setting.

Multimodal systems enhance diagnostic accuracy by combining data from different sources, thus enabling a comprehensive evaluation of facial paralysis. Heng et al. [41] designed a multimodal deep-learning framework that integrates image and video data to detect facial palsy. Using static and dynamic characteristics, the model could detect subtle changes in facial expressions that single-modality methods often miss. This integration significantly enhanced performance and demonstrated robustness in real-world applications. However, challenges in effectively fusing heterogeneous data types remained a limitation, requiring further optimization.

Nguyen et al. [42] used 3D point clouds for facial expression recognition, introducing geometric deep-learning techniques to analyze spatially distributed facial structures. Geometric deep learning allows capturing detailed measurements of facial asymmetry and movements, providing high accuracy in controlled environments. Though it is a novelty, the whole system depends on 3D datasets, requiring specific equipment and expertise to collect and process that data.

Gogu and Sathe [13] proposed an ensemble stacking model that utilized different feature extraction techniques: FAUs, landmarks, and eye-related features. This composite approach leveraged the strength of different methods and had a detection accuracy of 97.7% and a grading accuracy of 88.2%. The model was robust across different datasets and benefited from feature fusion; however, the problem of balancing efficiency with complexity remained a critical challenge to be addressed.

b. Real-Time Applications

Telemedicine and real-time features have drastically changed how the diagnostic tool is accessed, especially in isolated and less privileged areas. Chandaliya et al. [43] formulated the Tele Stroke System, which allows remote diagnosis and the treatment of stroke-related paralysis of the face. That system combines video conferencing, imaging technologies, and electronic health record systems, enabling the healthcare expert to examine the patient's condition in real-time. The TSS dramatically enhanced treatment outcomes by supporting timely interventions, establishing that telemedicine can reduce the issues associated with accessibility.

Kim et al. [18] presented a smartphone-based system for real-time facial paralysis detection by exploiting the classification ability of machine learning models regarding the severity of the condition. The system utilized facial image capture and preprocessing for reliability across various conditions. The method was excellent in diagnostic accuracy but faced issues with environmental changes like lighting and glasses or other facial accessories. Such difficulties underscore the need for efficient preprocessing algorithms to improve real-world practical applicability.

Multimodal and hybrid systems are a giant leap in facial paralysis recognition. They offer enhanced diagnostic capability by integrating multiple data types and methodologies. They combine static, dynamic, and 3D data for better coverage of facial features, enhancing the accuracy and robustness of assessments. Telemedicine and real-time applications have made these technologies reach patients' doorsteps in remote areas. Notwithstanding their promise, various challenges need to be addressed, such as data fusion, computational complexity, and environmental variability, to improve their performance and scalability. Future research should focus on improving multimodal integration methodologies, enhancing real-time processing capabilities, and ensuring smooth integration into clinical workflows to ensure broad acceptance.

III. DISCUSSION

It has been found from the literature review that there has been significant progress in the diagnosis of facial paralysis and that it is changing from traditional manual methods to sophisticated methods, which involve ML, DL, and multimodal systems. Traditional grading systems such as HB and Sunnybrook are widely used due to their simplicity and familiarity among clinicians, but they are subjective and have a potential for inconsistency. Instrumental grading techniques, such as EMG and advanced imaging modalities, are objective but suffer from problems in terms of cost, accessibility, and invasiveness. The constraints force a need for automated and scalable solutions, making the integration of ML and DL methodologies inevitable.

Machine learning-based methods are the middle step between traditional and deep learning. Feature-based methods, such as methods based on facial landmarks and geometric relationships, show efficiency and simplicity using handcrafted features. Still, the approach suffers from reduced scalability and generalization. Regression-based models give numeric estimates and are helpful tools for monitoring rehabilitation progress but rely on high-quality input features and curated datasets. These have formed foundations for more robust systems; however, they call for automation and the least dependence on feature engineering.

Methods based on deep learning, especially CNN, have succeeded by automating the feature extraction process and enhancing precision. Models such as DenseNet201, described in Veeravalli et al. [25], have performed remarkably wellclassifying facial paralysis using dense connectivity to allow feature reuse. Hybrid models that integrate CNNs and GANs, in the works of Sajid et al. [28], have managed to overcome limitations in datasets by enhancing generalization. However, the black-box nature of DL models and requirements for large, diverse datasets remain critical barriers to clinical adoption.

Advanced deep learning models, such as those using Long Short-Term Memory (LSTM) networks and Conditional Generative Adversarial Networks (CGANs), handle more complex aspects of facial paralysis detection. For example, Liu et al. [37] combined hierarchical networks with LSTMs for dynamic facial expression analysis and showed better capacity in capturing temporal dependencies. Similarly, Yaotome et al. [38] have used CGANs to synthesize facial paralysis expressions for better training data diversity. Such innovations highlight the possibility for DL models to overcome this limitation posed by traditional and ML-based methods, though computation demands remain and dataset diversity.

Multimodal and hybrid systems enhance the recognition of facial paralysis by combining data coming from different sources. For example, Heng et al. [41] combined image and video data, thus making detailed assessments of static and dynamic properties possible. Meanwhile, the telemedicine systems, including the TSS designed by Chandaliya et al. [43], using smartphone-empowered, real-time diagnostic tools that Kim et al. [18] proposed, highlight the ability to expand diagnostic serviceability in distant and impoverished communities. These systems aim to offset serious deficiencies in access; however, they face problems involving variability of environments, data fusion, and computation intensity.

Despite these promising advances, several challenges remain in all approaches. Large and diverse datasets are still unavailable, which restricts the generalization capabilities of ML and DL models. The black-box nature of DL models introduces problems in interpretation, and clinicians find it hard to trust and accept these systems. In addition, high computational demands and the inability to implement in real-time make large-scale deployment of advanced systems challenging in resource-constrained settings. Thus, the results show that though the basis is traditional, the use of ML and DL has a much more significant impact on accuracy, objectivity, and scalability. In addition, multimodal systems and telemedicine applications increase accessibility and applicability to real-world problems. Some of the future issues to be addressed are the issues of datasets, the explainability of models, and computational efficiency for making it applicable to real-world clinical implementation, thus making the facial paralysis recognition system reliable, real-time, and accessible.

IV. CONCLUSION AND FUTURE SCOPE

It had progressed from subjective scoring with the inspection to more complex ML and DL in face weakness detection. Standard scales like House-Brackmann and the Sunnybrook score establish a clinical scoring system, which unfortunately suffers from intra- and inter-individual variability and even less sensitivity to detection. The instrumental scores by electromyography or imaging are precise but costlier and often unavailable. Many of these mentioned limitations have been addressed by ML and DL methods, which provide automated and scalable solutions with high accuracy, especially CNNs, and other improved architectures, such as that of LSTM networks and the CGANs, which exhibit better performance in the categorization and dynamic assessment for facial expressions. Multimodal and hybrid systems, which have been developed by integrating data from various sources, have improved the capabilities of such diagnostic systems. On the other hand, the advent of telemedicine and real-time applications made access possible to far remote and under-served regions. Nevertheless, challenges include scarcity in the dataset, computational complexity, and black-boxed DL models. The intelligent system's integration into clinical workflow opens up enormous potential for upgrading diagnostic, grading, and rehabilitating facial paralysis.

Future research in facial paralysis recognition should address available challenges toward broader clinical adaptation and better patient outcomes. In that respect, large, diverse, and annotated datasets areessential to improve the generalizability and robustness of the ML and DL models. XAI frameworks would be essential to improve interpretability and trustworthiness in the DL systems, allowing clinicians to interpret and validate model predictions. Optimizing computational efficiency is essential to ensure real-time application occurs in resource-constrained environments. This opens further avenues for exploring multimodal systems in developing data types and their patterns, such as physiological signals and speech patterns, in more exhaustive evaluations. Integrating these intelligent systems with telemedicine platforms can revolutionize remote diagnostics and bring accessible, cost-effective healthcare solutions to fingertips. Therefore, this research in focus areas can further facilitate bridging technological innovations with clinical applications, making the developed facial paralysis recognition system reliable, efficient, and scalable in all diverse populations and parameters.

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