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Anxiety Level Analysis through Real Time Image

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Abstract- Anxiety is a mental illness that affects most people around the world. Early diagnosis and intervention are important for managing stress and improving personal health. Dental anxiety in children is a perennial concern and can be defined as the absence of feelings of fear, worry, anxiety or fear in an uncertain or unknown way. For this reason, the way to solve this anxiety in dentistry has been sought for a long time and it is important for the early detection of anxious children for the treatment of aggressive behaviour. The foundation for success in paediatric dentistry is behaviour management and the use of these behaviour management techniques to help children learn appropriate behaviour, problem-solving skills, stress reduction pressure, and facilitate appropriate oral therapy. Due to the burden of unmet expectations from parents, people and children, the use of behavioural management techniques in dentistry is constantly changing. This summary presents a new approach to stress detection using a convolutional neural network (CNN). CNN sequential model architectures are designed to extract important features from multiple sources and store expected physical properties in data. The model includes many convolutional techniques, additional techniques to reduce the size, and nonlinear activation functions showing nonlinearity. Training and testing data are separated to enable the performance model to be analysed. Various metrics, including accuracy, are used to evaluate the performance of continuously trained CNN models. The results of this project have important implications for early childhood depression research and interventions. The proposed CNN models are ranked from training and test data and show good results in stress detection.

Keywords- Anxiety detection, paediatric dentistry, Convolutional Neural Network (CNN), Sequential model, Train and test dataset, Deep learning.

I. INTRODUCTION

Early detection and precise depression diagnosis If this strategy is to be clinically beneficial, studies concentrating on personal level neuroimaging data analyses must be conducted, but the intrinsic difficulty of the information and its evaluation continues to be a barrier. Depressive disorder is an overall psychiatric disorder with an average lifetime prevalence of less than 20% in the population as a whole. It is linked to high rates of handicap, deficient mental health, and reduced life satisfaction, all of which serve as crucial criteria for selecting the best treatments and enhancing outcomes, thereby lowering the financial and psychological costs associated with hospitalisation, lost productivity at work, and suicide. The identification of psychiatric diseases, including depressive disorders, is exclusively based on inferences based on self-reported data and observed overall behaviour, guided by established categorization criteria (DSM-5).

Despite substantial advancements in dental techniques, technology, and materials, child patients worldwide still frequently experience anxiety associated with the dental office and certain treatments, which is thought to be a barrier to providing high-quality dental care. A significant advance in technology, artificial intelligence is now permeating the minds of academics all around the world. It is a branch of technological research that deals with computer science and the capacity of computers to easily complete tasks by simulating human brain function. Since it first entered the profession, dental science has undergone modernisation, from the retention of patient data records, diagnosis, and treatment planning, to the current ability for robots to execute surgery under the supervision of a physician. current situation.

Recent studies on the assessment of mental health have revealed that depression can be strongly indicated by one's facial features. Previous methods that relied on face analysis may be better at diagnosing depressive illnesses clinically. overcoming obstacles more effectively and objectively, preventing the visual perception of a complex depressive pattern. A frequent strategy is automated diagnosis of depression. To develop and execute real-time image-based depression level analysis in this project.

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II. LITERATURE REVIEW

In their study titled "Deep learning-based dental plaque detection on primary teeth: a comparison with clinical assessments," Wenzhe You et al. investigated the use of deep learning for detecting dental plaque on primary teeth. They compared the performance of their deep learning model with clinical assessments conducted by dental professionals. The results of their study indicated that the deep learning model demonstrated comparable performance to the clinical assessments in detecting dental plaque on primary teeth. This research suggests the potential of deep learning techniques as a valuable tool in dental plaque detection, offering a promising avenue for improving oral health assessment in pediatric dentistry.In this study, an AI model was developed to detect plaque on primary teeth, and its diagnostic accuracy was evaluated. The results of the study demonstrated that the AI model exhibited clinically acceptable performance in detecting dental plaque on primary teeth when compared to the assessments of an experienced pediatric dentist. This finding highlights the potential of AI technology to contribute towards enhancing pediatric oral health.

In their paper titled "Shaping the Future of Smart Dentistry: From Artificial Intelligence (AI) to Intelligence Augmentation (IA)," Hossein Hassani et al. conducted a comparative analysis to provide an overview of the current deployment of technology in dentistry and the potential roles of IA and AI in this field. They highlight that AI serves as an assistive tool in enhancing human capabilities. The challenges discussed include the integration of AI into routine dental practice, ensuring sufficient and reliable data input, addressing liability concerns, and managing the costs associated with new technology deployment. Looking ahead, the authors present insights on how future technologies can be integrated into everyday dental practice and how the interaction between robots and humans may evolve in light of ongoing technological advancements. The paper prompts discussions on the future direction of dentistry, questioning whether AI or IA will dominate the modern dentistry era.

In their clinical trial titled "The Efficacy of Little Lovely Dentist, Dental Song, and Tell-Show-Do Techniques in Alleviating Dental Anxiety in Paediatric Patients," Hira Abbasi et al. investigated the effectiveness of different techniques in reducing dental anxiety among pediatric patients. A total of 160 participants were divided into four groups: "little lovely dentist" mobile application, YouTube® dental video songs, "tell-show-do," and a control group. Dental prophylaxis treatments were provided to all participants, and anxiety levels were measured using heart rate and facial image scale before and after the treatment. The study revealed that mobile applications and dental video songs led to a significant reduction in heart rate and facial image scale scores, indicating reduced anxiety levels. However, the "tell-show-do" technique, which is commonly used, did not show significant benefits in reducing anxiety levels. The findings suggest that behavior modification techniques such as smartphone applications and dental songs can effectively alleviate dental anxiety in pediatric patients.

In their study titled "Preferences and Choices of a Child Concerning the Environment in a Pediatric Dental Operatory," C. Vishnu Rekha et al. aimed to identify children's preferences in a dental clinic to alleviate anxiety during dental procedures. The survey-based research involved 50 children aged 6-10 years. The findings revealed that a significant number of children preferred listening to rhymes and watching cartoons while undergoing dental treatment. Additionally, they expressed a preference for walls painted with cartoons, a dental chair filled with toys, a scented environment, and the presence of their parents during the treatment. These results provide valuable insights for dental teams in designing pediatric dental operatory rooms that create a comfortable environment, ultimately reducing anxiety in children and enhancing the quality of healthcare provided.

III. PROPOSED METHODOLOGY

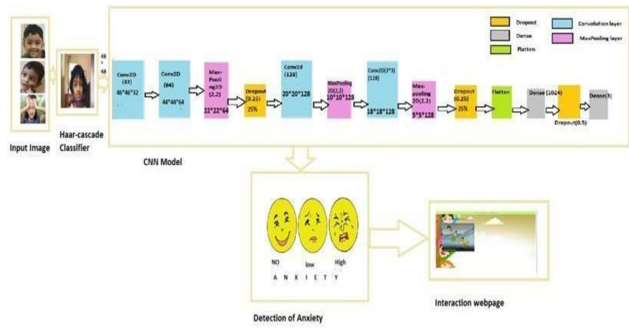

Fig 1. System Architecture

Data Gathering: We created dataset of facial images from children with and without anxiety, gather images from various sources such as online databases, controlled environments, and real-world scenarios. The dataset represents a wide range of individuals and includes variations in expressions, poses, and lighting conditions.

Preprocessing:We preprocess the collected facial images and improve their quality, follow these steps. Firstly, apply face detection algorithms to locate and isolate the faces in the images. Next, use face alignment techniques to normalize their orientation and alignment. Finally, enhance the images using image processing methods to reduce noise, adjust brightness, and improve contrast. These steps help ensure consistency and prepare the images for further analysis.

Train-Test Split:The train-test split is an essential step in anxiety detection projects, involving the division of the dataset into a training set and a testing set. The training set is used for model training with labeled examples, while the testing set is kept separate to evaluate the model's performance independently. This split is usually performed randomly, with common ratios like 70-30 or 80-20 for train-test respectively. The testing set should remain untouched until the final evaluation to ensure unbiased results. By assessing the model's performance on unseen data, we can gauge its ability to generalize and estimate real-world effectiveness. Cross-validation techniques can also be employed alongside the train-test split to further evaluate the model's efficacy. Ultimately, the train-test split is a crucial step enabling the development and evaluation of accurate and reliable anxiety detection models.

Haar Cascade Feature Extraction:Haar Cascade feature extraction is employed to analyze facial expressions and identify distinctive features associated with anxiety. The technique involves training a Haar Cascade classifier using positive samples containing anxiety-related facial expressions, along with negative samples that lack such expressions. By recognizing patterns and variations in facial characteristics like raised eyebrows or widened eyes, the classifier can detect cues indicative of anxiety. This approach facilitates the identification of anxiety-related cues in images or videos, facilitating the development of precise and dependable anxiety detection systems.

Feature Integration:Feature integration involves the combination of multiple features from various sources or modalities to create a comprehensive representation of anxiety-related information. This process aims to capture a holistic perspective of anxiety by considering physiological, behavioral, textual, or facial expression data. Techniques such as concatenation, weighted averaging, or feature fusion are utilized to merge these distinct features into a unified representation. Integrated features provide a more comprehensive understanding of anxiety, facilitating accurate and reliable detection and classification. To ensure successful integration, careful attention must be given to feature selection, normalization, and handling of missing data. Additionally, dimensionality reduction methods can be employed to enhance computational efficiency. Overall, feature integration optimizes anxiety detection models by incorporating diverse information sources, contributing to improved performance and insights.

CNN Sequential Model Design:We created a CNN sequential model architecture for anxiety detection, it is recommended to design a model that incorporates convolutional layers for capturing spatial patterns in the combined features, pooling layers for dimensionality reduction, and dense layers for classification. Experimentation with various layer configurations, activation functions, and regularization techniques can be performed to optimize the model's performance. By customizing the architecture, activation functions, and regularization methods, the model can effectively learn and extract meaningful features from the combined input, leading to improved accuracy in anxiety detection.

Model Training:To train the CNN sequential model using the training dataset for anxiety detection, it is important to define a suitable loss function, such as binary cross-entropy, and select an optimization algorithm, such as Adam or SGD, to iteratively update the model parameters. Experimentation with different hyperparameters, including learning rate, batch size, and number of epochs, is essential to optimize the model's performance. By customizing these hyperparameters, the model can effectively learn from the training data, minimize the loss function, and improve its ability to accurately classify individuals with and without anxiety.

Model Evaluation:To evaluate the trained model for anxiety detection, it is crucial to assess its performance using the testing dataset. This evaluation involves calculating various metrics such as accuracy, precision, recall, and F1-score to quantify the model's effectiveness in classification. Additionally, conducting additional analyses like the ROC curve and calculating the area under the ROC curve (AUC-ROC) can help evaluate the model's discrimination power. By analyzing these metrics and assessments, we can gain insights into the model's performance, its ability to correctly identify individuals with and without anxiety, and its overall effectiveness as an anxiety detection tool.

Model Deployment:To deploy the trained model for anxiety detection applications, it is essential to develop an interface or application that accepts new facial images as input and provides anxiety predictions using the trained model. The deployment process should focus on efficiency, user-friendliness, and scalability. This involves designing an intuitive interface that allows users to easily upload or capture facial images for analysis. The deployed system should efficiently process the input images, apply the trained model for anxiety prediction, and display the results in a clear and understandable format. Additionally, ensuring scalability allows the system to handle a growing number of users and effectively manage the computational resources required for anxiety detection. By prioritizing these aspects, the deployment can provide a valuable and accessible tool for anxiety detection in real-world applications.

Continuous Improvement:To continuously enhance the anxiety detection system, it is crucial to focus on refining the training process and model architecture. This can be achieved by augmenting the dataset with new samples to increase its diversity and coverage. Additionally, exploring transfer learning techniques allows leveraging pre-trained models on related tasks to boost performance. Incorporating additional data modalities, such as textual or physiological data, can provide complementary information for more accurate anxiety detection. Regular experimentation and analysis of different training methods, architectural modifications, and data enhancements are key to improving the model's performance and generalizability over time. By iteratively refining the system, it becomes more robust and effective in accurately identifying anxiety in individuals.

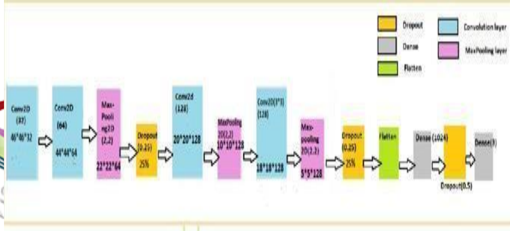

Fig 2. CNN Model

IV. RESULT

The graph tends to show the accuracy achieved in 100 epochs . The accuracies achieved at 100 epoch is around 73% which depicts the overall accuracy achieved after trainings the model.

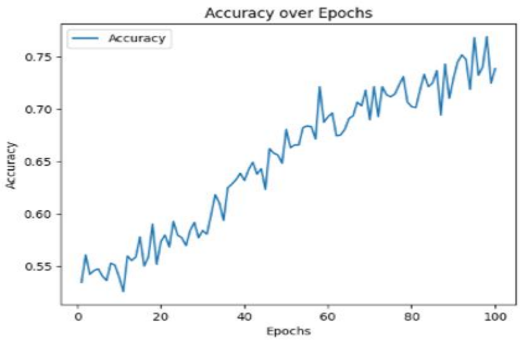

Fig. 3. CNN Classification Accuracy Graph

Accuracy Rate = TP/Total number of instances
Error Rate = 1 − Accuracy Rate
Precision = TP / (TP + FP)
Recall = TP / (TP + FN)
F1 Score = 2*(Precision*Recall) /Precision Recall
Whereas,
TP = True positive
FN= False Negative
FP = False Positive
TN = True Negative
Existing System Proposed System(CNN)
Precision 60.6 52.70
Recall 75.1 87.64
F-Measure 68.8 74.31
Accuracy 78.29 86.26

Table No 1.Method Comparison

	Existing System	Proposed System(CNN)
Precision	60.6	52.70
Recall	75.1	87.64
F-Measure	68.8	74.31
Accuracy	78.29	86.26

Fig 4 Sample Output

V.CONCLUSION

The model uses layers to capture spatial and temporal patterns and lets it learn discrimination for stress detection. The training process includes defining the appropriate loss function, optimising the algorithm, and tuning hyperparameters to improve the performance of the model. Evaluate the training model using test data to evaluate its performance. Metrics such as accuracy, precision, recall, and F1 score are calculated to evaluate the effectiveness of the stress perception model. These measures provide insight into the model's ability to identify stressful situations and avoid negative and negative situations. The results show the potential of the method to detect stress. The CNN model demonstrated its ability to detect stress based on faces, consistently achieving accuracy, precision, recall, and F1-score. This stress test should be widely used in mental health services. By automating the search process, it can help identify stress at an early stage and provide timely support and human intervention. The combination of Haar Cascade feature extraction and the CNN sequence model provides a way to use local and global spatiotemporal models of the face to improve performance.

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