Development of an Epilepsy Monitoring System in Real Time Using MediaPipe and Deep Learning Techniques

Report Submitted

by

M Gopinath

(2022BMM1005)

DEPARTMENT OF BIOMEDICAL ENGINEERING

INDIAN INSTITUTE OF TECHNOLOGY ROPAR

Development of an Epilepsy Monitoring System in Real Time Using MediaPipe and Deep Learning Techniques

Abstract:

Epilepsy, a neurological disorder characterized by unpredictable seizures, affects millions worldwide, with a significant impact on mortality and quality of life. This report introduces a real-time epilepsy monitoring system leveraging MediaPipe and deep learning, targeting enhanced epilepsy management. Addressing challenges related to medication adherence and inadequate seizure diaries, the system's precision in identifying seizures from video data promises transformative impact, particularly in resource-constrained settings.

***Keywords**:* Epilepsy Monitoring System, MediaPipe, Deep Learning, Seizure Detection.

1) Introduction:

1.1 Epilepsy :

Epilepsy is a neurological disorder that affects the brain's electrical activity and causes seizures. Seizures are sudden surges of electrical activity in the brain that can result in involuntary movements, confusion, and sometimes loss of consciousness. Epilepsy can affect people of different ages and backgrounds. It is estimated that 50 million people worldwide, or 1% of the population, have epilepsy [1], [2] . However, not all people who have seizures are considered to have epilepsy. Epilepsy is one of the most common and serious neurological conditions globally, and it is the third most prevalent neurological disorder in India. Unfortunately, more than 80% of people with epilepsy in India and other low- and lower-middle-income countries (LMICs) do not receive adequate treatment [3] , [4]. Epilepsy also has a significant impact on mortality. According to [5] epilepsy causes 32,000 premature deaths in India and 1,25,000 premature deaths worldwide every year.

1.2 Importance of Medication Adherence

Medication adherence is crucial for the management of epilepsy, as poor adherence can have serious consequences. Anti-seizure medication non-adherence further increases the risk of death for people with epilepsy who are already at a higher risk than the general population. Non-adherence can also lead to more seizures, emergency visits, and health care costs, which may be partly due to intrinsic factors or associated comorbidities. The risk of premature death was 2.9 times higher in people with epilepsy than in the general population [6]. Non-adherence to anti-seizure medications was associated with a more than threefold higher risk of death compared to adherent patients. To improve outcomes and reduce mortality, it is important to identify the characteristics that predict poor adherence and implement targeted strategies to enhance adherence. Additionally, poor adherence to long-term medications affects the effectiveness of treatment, making this a major public health issue in terms of quality of life and health economics. Appropriate treatment plans and clear communication strategies are essential to improving self-management and awareness of epilepsy among patients.

1.3 Importance of seizure diaries

A seizure diary is a type of patient-reported outcome that allows patients to record their seizure events and identify any potential triggers. Avoiding known triggers can help reduce the frequency of seizures in some cases [7]. A seizure diary can also help the patient and the clinician monitor the seizure activity and characteristics, such as duration, frequency, and recovery, as well as the triggers. Therefore, accurate reports or recordings of seizure activity are useful for the diagnosis and treatment of epilepsy [8]. It is preferable to use an electronic diary rather than a paper one, but many patients in rural India do not have access to smartphones, which limits this option. Moreover, a Nielsen study (a global company for audience measurement, data, and analytics) found that there is a low level of digital literacy in rural India, which would need to be improved to use a smartphone application for seizure diary recording. Additionally, the unreliable and non-existent internet connectivity in rural areas of India makes it difficult for patients to access and use a mobile application for seizure diary recording. Given these challenges, it may be better to combine digital and non-digital tools, such as paper-based diaries or text messages, to provide a wider range of patients with seizure diary methods that suit their needs.

2) Literature Review

Medication is the most common way of treating epilepsy. Doctors usually start by recommending a few medications, and if additional remedies are needed, they might recommend alternative medications. It's critical to record medication history, seizure potential trigger factors, and other seizure occurrence information to make sure prescribed drugs function as intended. The physician would find it extremely difficult, if not impossible, to keep track of this patient information on a regular basis. This highlights how important it is for the patient to maintain a notebook or diary in order to record details about their drug history and seizure occurrences. It might be difficult for the doctors to interpret these handwritten notes, even if the patient writes down all of these details [9]. The advent of smartphone applications for keeping a digital log of seizure occurrence information somewhat allays these worries. Certain programs, such as Seizure Sync, EpApp [10], and EpiWatch, have reminders for taking medicine and keeping seizure diaries.

Epilepsy not only affects the individual suffering from it, but also has a significant impact on their family and community. The unpredictable nature of seizures can pose physical risks, while societal attitudes towards epilepsy can lead to social exclusion and stigma. For instance, children with epilepsy may be barred from attending school, adults with epilepsy may face restrictions on marriage, and employment opportunities may be denied, even when seizures would not pose a risk in the workplace. Furthermore, epilepsy is associated with serious psychological consequences, including increased levels of anxiety, depression, and low self-esteem compared to those without the condition.

The treatment gap in epilepsy is largely due to issues such as limited access to healthcare services, inadequate funding and resources for epilepsy care, and a lack of epilepsy education and training for healthcare professionals. As a result, many people with epilepsy do not receive an accurate diagnosis or have access to effective treatment, leading to increased morbidity and mortality and a reduced quality of life. The treatment gap in India is estimated to be between 50 and 80% [11].

To close this treatment gap, it is necessary to increase awareness and education about epilepsy, improve access to healthcare services, develop appropriate treatment standards and protocols, and strengthen health systems and infrastructure. The World Health Organization recommends involving primary healthcare providers in the management of epilepsy [12], suggesting that community-level interventions could help close the treatment gap and ensure that people with epilepsy receive the appropriate care and treatment.

The study Aberrant Epileptic Seizure Identification: A Computer Vision Perspective reveals challenges in accurately identifying unusual seizure patterns [13]. The research encountered low classification accuracy due to supervised learning's dependence on training data that didn't cover these unique patterns, hindering the model's adaptability. Specifically, within cross-validation, the model struggled to effectively classify the semiology of patients exhibiting aberrant seizures. Capturing and representing these atypical patterns within the training dataset proved challenging, limiting the model's ability to generalize.

The hierarchical multimodal system integrates computer vision algorithms and deep learning models to concurrently analyze facial expressions, body movements, and hand gestures observed in 2D monitoring videos[14].The results demonstrate the system's effectiveness in classifying types of epilepsy by analyzing facial, body, and hand motions, showcasing accuracies ranging from 12% to 83.4%, 41.2% to 80.1%, and 32.8% to 69.3%, respectively.

To address these limitations, future directions include exploring novel model architectures like unsupervised or semi-supervised learning methods to handle unseen or unusual epilepsy seizure patterns. The model's overall generalization should be improved by adding more diverse training datasets that cover a wider range of seizure types, including cases that don't follow the rules. Additionally, creating adaptive learning frameworks that can change model representations on the fly to accommodate new or previously unseen seizure patterns could be a way to improve classification accuracy in these tough situations.

3) Methodology

3.1) Data Acquisition

Our study leverages video recordings acquired from Parmar Hospital in Ropar, totaling 77 minutes and 32 seconds in duration. These recordings capture a wide range of activities, including normal instances and seizure episodes, at a consistent frame rate of 25 frames per second (fps). In addition, an additional 170 minutes and 12 seconds of normal data was personally recorded, also maintaining the 25 fps frame rate. This augmentation extended the dataset's total duration to 247 minutes and 48 seconds, enhancing its diversity for comprehensive analysis and model development.

3.2) Mediapipe Holistic Module

The integration of the Mediapipe Holistic module was crucial in precisely extracting landmark points associated with various body aspects, encompassing facial expressions, body poses, and hand gestures from every frame of the video. According to details from the Mediapipe documentation, this module combines elements from the pose, face, and hand landmarks to create a comprehensive human body landmarker. It enables the analysis of complete-body gestures, poses, and actions by leveraging machine learning models on a continuous stream of images. The model incorporates convolutional neural networks (CNNs) and regression models to detect and localize body parts within the video frames. These networks employ convolutional layers, activation functions like ReLU, pooling layers, and fully connected layers to process visual data and learn representations of body landmarks. These backend formulas and techniques work synergistically within the Mediapipe holistic model to accurately extract landmark points related to different body parts during real-time video processing. Notably, this task outputs a total of 543 landmarks in real-time, comprising 33 pose landmarks, 468 face landmarks, and 21 hand landmarks per hand.

Fig. 1: Human Body Landmark Point Extraction using MediaPipe Holistic Module

However, for our model's application, we specifically extracted a subset of these landmarks, focusing on 21 face landmarks, 42 hand landmarks (21 per hand), and 33 pose landmarks—accumulating to a total of 96 landmarks out of the available 543. This selective extraction process allowed us to capture key features pertinent to our research focus while streamlining computational requirements and ensuring efficient processing of the video data.

3.3) Data Preprocessing for Quality Assurance

The preprocessing stage post-landmark extraction involved three critical steps: handling missing data, addressing class imbalances through SMOTE techniques, and segmentation and sequential data preparation.

1. Handling missing data:

In this process, our model systematically removed instances of missing or unreliable information, represented as NaN values, ensuring the dataset's quality and integrity.

2. SMOTE Technique:

SMOTE involves identifying samples from the minority class and applying transformations in the feature space to create new synthetic instances. These changes, which are usually controlled by k-nearest neighbors and statistical analysis, make new data points that look like the existing minority class instances while keeping the main features of the originals.

To address the class imbalance between normal activities and seizure episodes, the Synthetic Minority Over-sampling Technique (SMOTE) was employed. Our model, which uses SMOTE to generate synthetic instances for the minority class, specifically seizure episodes in this instance, was pivotal in expanding the dataset from 81,378 to 290,389 frames. This augmentation was fundamental to ensuring a balanced representation during model training, effectively mitigating concerns related to model overfitting and biases inherent in imbalanced datasets.

3. Segmentation and Sequential Data Preparation:

Our proposed model segmented the rebalanced dataset, comprising 580,778 frames, into fixed time steps (5 seconds) with a specified overlap (2.5 seconds). Each segment, comprising 125 time steps and 321 features, captured distinctive instances and was associated with binary labels based on the presence or absence of seizure instances within that time frame. Sequential chunks of data were meticulously prepared, aiming to feed these segments into a machine learning model for seizure detection. This methodology ensures comprehensive data representation, providing a robust foundation for subsequent model development and evaluation.

The proposed approach ensures a comprehensive representation of data, laying a solid foundation for subsequent model development and evaluation. This systematic method encompasses pivotal stages of data acquisition, preprocessing, and feature engineering, illustrating an organized framework for detecting seizures in video data.

3.4) Sequential Processing and Nonlinear Transformations

The inclusion of Long Short-Term Memory (LSTM) layers is pivotal for temporal sequence analysis. LSTMs excel at capturing dependencies and patterns over time, making them ideal for tasks requiring sequential data analysis, such as video processing or time-series prediction.

Our neural network's sequential processing commences with two LSTM layers, denoted as LSTM (1) and LSTM (2), each comprising a varying number of units defined by the hyperparameter search.

In our model's LSTM architecture, the strategic inclusion of the forget gate stands as a crucial element for managing sequential data. This gate governs the removal of information from the cell state, primarily regulated by the sigmoid activation function:

$$ft = \sigma(Wf \cdot [ht - 1, xt] + bf)$$

Where ft signifies the output of the forget gate at time step t.

ht denotes the previous hidden state.

xt represents the current input.

Wf refers to the weight matrix governing the forget gate.

BF represents the bias term associated with the forget gate.

Adding the LeakyReLU activation function between the LSTM layers with an alpha (π) value of 0.5 creates nonlinearity, which makes it easier to represent and extract features in the temporal domain.

3.5) Spatial Feature Extraction and Dimensionality Reduction

The attention mechanism embedded within our model systematically identifies and accentuates essential spatial elements within the extracted features. By giving attention weights to different spatial features on the fly, the model can effectively highlight and prioritize important elements, making it easier to extract spatial features and reduce the number of dimensions.

3.5.1) Advanced Attention Mechanism for Spatial Feature Extraction

Our proposed model integrates a custom attention mechanism that has been meticulously designed to highlight and prioritize specific elements crucial for processing within the context of our model. The custom attention layer, an integral part of our deep learning network, operates by computing alignment scores and deriving attention weights, a process vital for directing the model's focus towards relevant temporal features.

3.5.1.1) Computation of Alignment Scores

The foundation of our attention mechanism rests upon the computation of alignment scores, achieved through the application of a hyperbolic tangent (tanh) function:

$$e=\tanh(W \cdot x+b)$$

Here, e signifies the derived alignment scores resulting from the input sequence (x) transformed by the weight matrix (W) and the bias term (b). These scores unveil the relative importance of each element within the sequence, allowing the model to discern and highlight spatially significant features.

3.5.1.2) Generation of Attention Weights

The alignment scores undergo a softmax operation to generate attention weights, enabling the model to assign precise importance to individual sequence elements:

$\beta = \text{softmax}(e)$

The generated attention weights (β) serve as a mechanism to emphasize the significance of each element within the sequential data. These weights guide the model in constructing a context vector, consolidating the contributions of elements based on their respective attention scores:

$\text{Context Vector} = x \times \beta$

To put it simply, this attention mechanism, which can calculate alignment scores, attention weights, and a context vector, makes it much easier for our model to focus on and process the most important temporal features in the sequential data. This custom attention mechanism makes it much easier for the model to find relevant spatial features. This sets the stage for better performance in tasks that involve spatial analysis and spatial data interpretation.

3.5.2) Spatial Pattern Recognition via Convolutional Layers

In our proposed model, convolutional layers serve as a fundamental component, extracting crucial spatial features from input data to complement temporal analysis. These layers excel at identifying intricate patterns and structures within spatial arrangements, proving invaluable for applications like image recognition and video understanding.

Convolutional Layer Configurations:

Conv1D Layer 1:

- Filters: Ranging between 64 and 256
- Kernel size: 5
- Strides: 2
- Activation: ReLU

MaxPooling1D, Layer 1:

- Pool size: 2
- Strides: 2

The subsequent MaxPooling1D layer effectively reduces dimensionality while retaining vital spatial information.

Conv1D Layer 2:

- Filters: Ranging between 32 and 128
- Kernel size: 3
- Strides: 1
- Activation: ReLU

MaxPooling1D Layer 2:

- Pool size: 2
- Strides: 2

This subsequent MaxPooling1D layer further reduces dimensionality, enhancing computational efficiency while preserving essential spatial features.

Our proposed Convolutional Neural Network model relies on the operations and configurations of these Conv1D and MaxPooling1D layers. Their ability to capture intricate spatial patterns significantly amplifies the model's capability in discerning complex spatial nuances, crucial for tasks like video understanding and spatial data interpretation. The model can understand both the temporal and spatial aspects of the input because it uses both LSTM and convolutional layers. This gives a full picture of the complex patterns in the data.

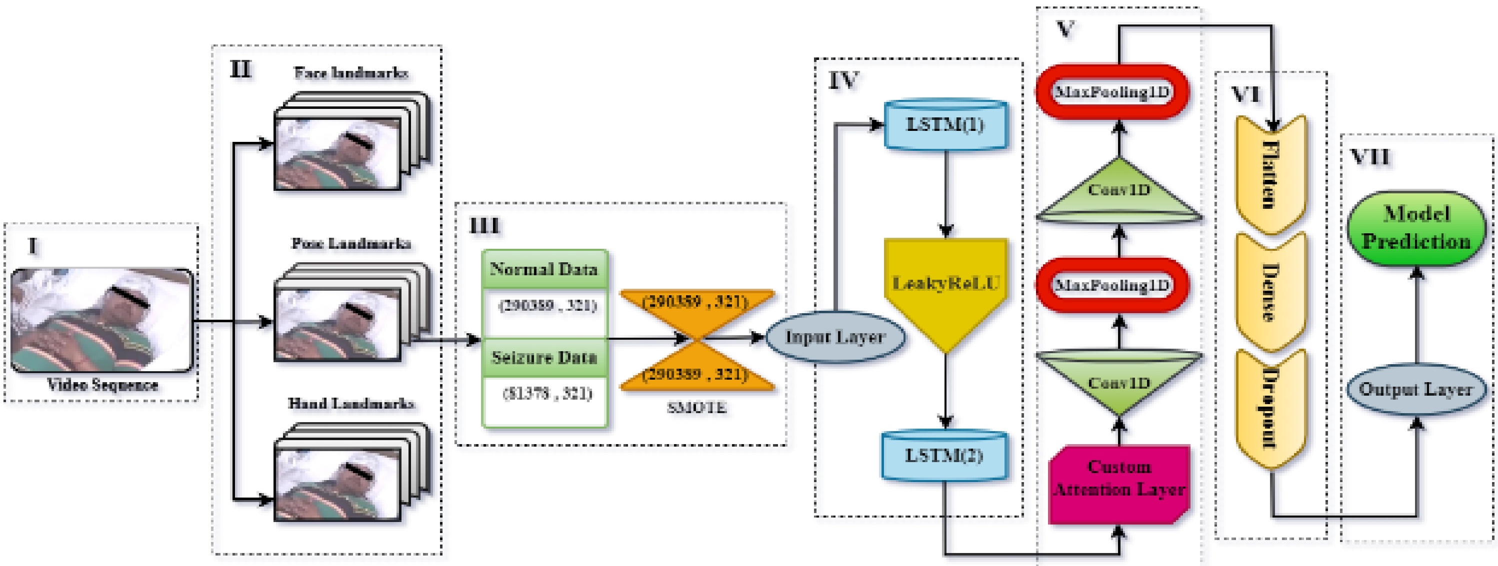

Fig.2 : A schematic diagram of proposed approach for Epilepsy Monitoring System in Real Time Using MediaPipe and Deep Learning

3.6) Classification and Regularization

This section contains the network's final structure, which has been fine-tuned for accurate classification and includes key regularization methods. The sequence after the flatten layer orchestrates data transformation, enabling efficient classification through subsequent layers.

The dense layer, which is the most important part, combines features, using its ability to synthesize information and allow nonlinear transformations that are good for classification tasks. Its flexible unit configuration, which ranges from 32 to 128 units, lets it handle complex feature representations. This makes the model better at figuring out the complex patterns that come up in seizure detection tasks.

In parallel, the dropout layer acts as a strategic defense mechanism against overfitting, strategically engaged to bolster model resilience during training. This layer adds controlled randomness to the network by turning off some neurons selectively. This stops the model from relying too much on certain pathways and makes it better at generalization. The model can carefully balance complexity and regularization with the variable dropout rates, which range from 0.2 to 0.7 with steps of 0.1. This is an important part of reducing the risk of overfitting in complex datasets.

This neural network architecture is used for the final classification and regularization step, where the high-level features are utilized for decision-making. Sequential processing and nonlinear transformations, spatial feature extraction and dimensionality reduction, classification, and regularization all work together to create a structured framework that is essential for building our proposed model that can find seizures in video data.

3.7) Hyperparameter Tuning and Evaluation

To fine-tune our model's performance, a hyperparameter tuning process was undertaken, harnessing the power of the Hyperband algorithm, which combines random search with successive halving to efficiently explore the hyperparameter space. This algorithm's efficiency lies in its ability to intelligently allocate computational resources while progressively focusing on promising hyperparameter configurations. This repeated exploration of the hyperparameter space finds the best values for important parts of the Adam optimizer, like the LSTM units, convolutional layers, dense units, dropout rates, and learning rates. The objective is to configure the neural network with the most effective combination of parameters tailored for precise seizure detection in video data.

The training phase involves iterating over the dataset for 50 epochs, enabling the model to learn and refine its internal representations based on the training data. Post-training, the model undergoes evaluation using an 80-20 split of the dataset into training and testing subsets. This approach facilitates a robust assessment of the model's performance and its ability to generalize to unseen data. The tuner explores various configurations to identify the optimal set that maximizes the model's classification accuracy and generalization capabilities. The model is much better at finding complex patterns and time- and space-dependent relationships in video data after these hyperparameters have been tuned and attention mechanisms have been added.

Moreover, within the final model architecture, the output layer is pivotal. Tailored for binary classification, this layer utilizes the sigmoid activation function, providing a binary output. This setup makes sure that the model's prediction output is good for finding seizures by giving a clear binary signal that shows whether there were seizure instances in the analyzed video segments or not.

The final model, with its well-tuned architecture and hyperparameters, demonstrates a substantial understanding of spatial-temporal dependencies in video data. Its high precision in detecting seizure instances while minimizing false positives positions it as an effective tool in clinical applications for seizure monitoring and detection.

4) Results and Evaluations :

4.1) Model Performance Analysis and Validation Findings:

Our model's performance revealed promising outcomes across various evaluation metrics. During the initial 12 epochs, the model showcased consistent performance, achieving a training accuracy of 96.76% and a validation accuracy of 96.80%. Subsequent epochs demonstrated further enhancement, culminating in a notable training accuracy of 98.01% and a validation accuracy of 96.66%. The evaluation of the test dataset yielded compelling results, with the model achieving an accuracy of 96.69% and a loss of 0.0809. These findings underscore the model's robustness and its ability to generalize effectively.

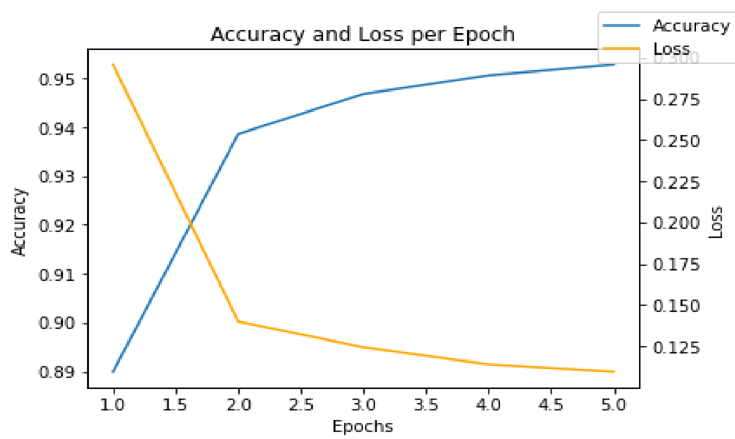

Fig.3: Representation of training and validation accuracy and loss of model

4.2) Comparison with Baseline Models and Benchmarking Results:

1. Normalized Confusion Matrix :

A comprehensive evaluation was conducted through a normalized confusion matrix. This matrix precisely delineates the true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), offering crucial insights into the model's proficiency in accurately discerning between our target classes: Normal (0.0) and Seizure (1.0). Our model exhibited commendable performance, correctly identifying 923 instances as positive (TP) and accurately labeling 893 instances as negative (TN), indicating robustness in predicting both classes. However, there were 27 instances misclassified as positive (FP) and 31 instances mislabeled as negative (FN), highlighting specific areas necessitating model refinement.

Additionally, the substantial Area Under the Curve (AUC) value of 0.9962725594749795 validated the model's exceptional discriminatory ability. This metric underscores the model's effectiveness in distinguishing between the two classes across diverse classification thresholds, affirming its reliability.

The visual representation of the normalized confusion matrix, presented as a heatmap, showcased balanced precision and recall for both classes. This graphical depiction emphasizes the model's adeptness in correctly identifying instances from each class while pinpointing potential areas for optimization or further investigation.

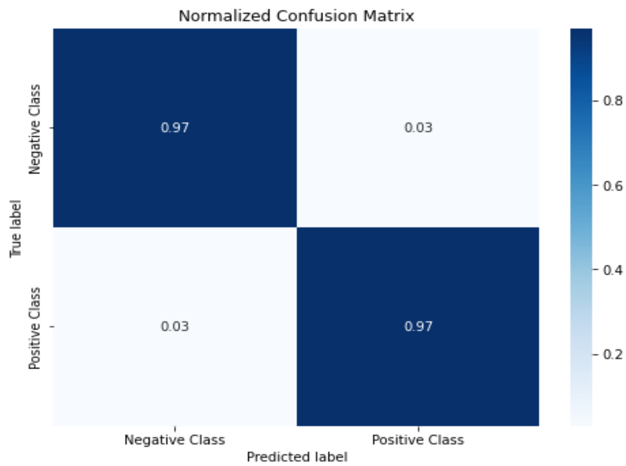

Fig.4: Representation of Normalized confusion matrix

2. Precision-Recall Curve:

The precision-recall curve serves as a vital evaluation tool, depicting the intricate balance between precision and recall within our model's performance. It's a graphical representation that showcases how the model's predictions balance precision (the proportion of true positives among all predicted positives) and recall (the proportion of true positives identified correctly).

The average precision (AP) metric of 0.97 obtained from this curve signifies the model's proficiency in maintaining high precision while also effectively recalling relevant instances. This metric holds significance in scenarios where class imbalances exist or when both precision and recall are crucial, as in our case of detecting seizure instances in video data.

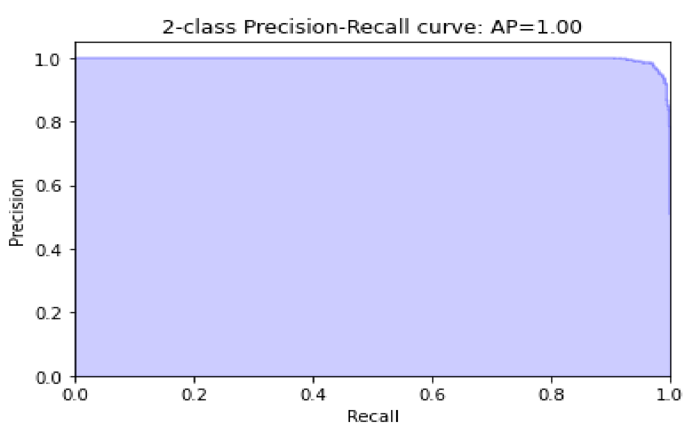

Fig 5: Representation of Precision Recall Curve

3. Calibration Curve:

The calibration curve serves as a crucial tool to assess the reliability and consistency of the model's predicted probabilities against the actual occurrence of events. In the context of seizure detection within video data, it plays a pivotal role in evaluating the model's predictive confidence and assessing the trustworthiness of its probability estimates. The 45-degree diagonal line, depicted as the gray dashed line, represents ideal calibration. Any deviations from this line in the calibration curve indicate potential issues in the model's calibration. If the curve diverges from this ideal line, it suggests that the model might exhibit overconfidence or underconfidence in its predictions. Overconfidence might lead to excessively certain predictions, potentially resulting in false alarms, while underconfidence might cause missed seizure instances.

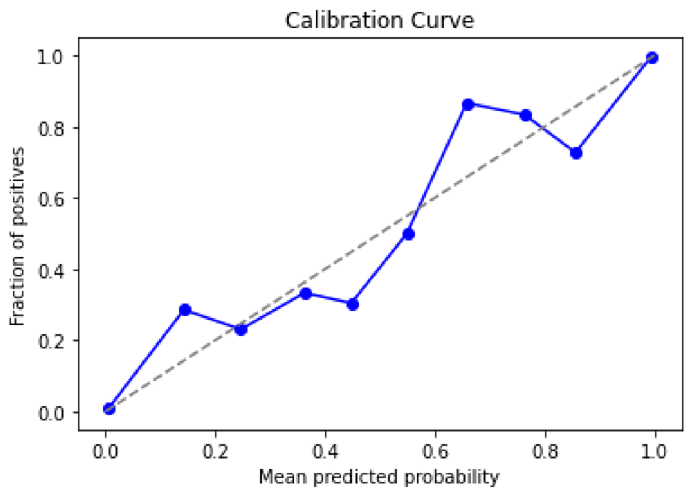

Fig 6: Figure showing calibration curve

Conclusion and future scope:

The development of this real-time Epilepsy Monitoring System, empowered by MediaPipe and Deep Learning techniques, embodies a significant stride towards personalized, efficient epilepsy management. Its precision in identifying seizures from video data serves as a beacon of promise in addressing challenges related to medication adherence and inadequate seizure diaries. Beyond its performance metrics, the system's potential to bridge the treatment gap in resource-constrained settings heralds a transformative impact in neurological disorder management.

Our Epilepsy Monitoring System represents a monumental stride towards tailored, real-time monitoring, and management strategies. Its promise to revolutionize epilepsy care, especially in marginalized communities, paves the way for transformative advancements in neurological disorder management via technology-driven solutions.The evolution of our system depends on enhancing its adaptability and precision in recognizing a wider array of seizure patterns. Diversification of datasets, novel learning methodologies, and the integration of multimodal data will enhance the system's diagnostic capabilities.

Bibliography:

[1] C. E. Stafstrom and L. Carmant. Seizures and epilepsy: An overview for neuroscientists. Cold Spring Harb. Perspect. Med, 5(6), June 1992.
[2] S. D. Shorvon R. H. Ellison S. M. Cascante M. Placencia, J.A.W.S. Sander. Epilepsy, available: https://www.who.int/news-room/fact- sheets/detail/epilepsy. June 1992.
[3] Singh G Sander JW Singh B, Mahajan N. Temporal trends in the epilepsy treatment gap in low- and low-middle-income countries: A meta-analysis. J Neurol Sci., 2022.
[4] Krishnan A Dua T d'Aniello F Manzoni S Sander JW Singh G, Sharma M. Models of community-based primary care for epilepsy in low- and middle-income countries.
Neurology, 2020.
[5] India state-level disease burden initiative neurological disorders collaborators. The burden of neurological disorders across the states of india: the global burden of disease study. 2021.
[6] C. A.; Greene J Malek, N.; Heath. A review of medication adherence in people with epilepsy. Acta Neurologica Scandinavica, 2016.
[7]Anonymous._seizure_diaries_https://epilepsysociety.org.uk/about-epilepsy/epileptic-seizures/seizure-diaries._2022.
[8] Recording seizures and seizure diary_https://epilepsyfoundation.org.au/understanding-epilepsy/. 2022.
[9] D. E.; DiVentura B.; Vannest J.; Hixson J. D.; Moss R.; Herman S. T.; Fureman B. E.; French J. A Fisher, R. S.; Blum. Seizure diaries for clinical research and practice: Limitations and future prospects. Epilepsy amp, 2012.
[10] S.; Beavis E.; Gill D.; Bye A. M. E Le Marne, F. A.; Butler. Epapp: Development and evaluation of a smartphone/tablet app for adolescents with epilepsy. Journal of Clinical Neuroscience, 2018.
[11] Newton CR Carter JA Mbuba CK, Ngugi AK. The epilepsy treatment gap in developing countries: a systematic review of the magnitude, causes, and intervention strategies. Epilepsia, 2008.
[12] Organization wh. epilepsy: A public health imperative. 2008.
[13]Ahmedt-Aristizabal, D., Nguyen, K., Denman, S., Sarfraz, M. S., Sridharan, S., Dionisio, S., & Fookes, C. (2019, July). Vision-based mouth motion analysis in epilepsy: A 3d perspective. In 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) (pp. 1625-1629). IEEE.
[14] Ahmedt-Aristizabal, D., Fookes, C., Denman, S., Nguyen, K., Fernando, T., Sridharan, S., & Dionisio, S. (2018). A hierarchical multimodal system for motion analysis in patients with epilepsy. Epilepsy & Behavior, 87, 46-58.
[15] Siam, A. I., Soliman, N. F., Algarni, A. D., El-Samie, A., Fathi, E., & Sedik, A. (2022). Deploying machine learning techniques for human emotion detection. Computational intelligence and neuroscience, 2022.

[16] Ahmedt-Aristizabal, D., Fookes, C., Nguyen, K., Denman, S., Sridharan, S., & Dionisio, S. (2018). Deep facial analysis: A new phase I epilepsy evaluation using computer vision. Epilepsy & Behavior, 82, 17-24.

[17] National health systems resource center ab. comprehensive primary care through health and wellness clinics. 2018.

[18] Nandraj S et al Patel V, Parikh R. Assuring health coverage for all in india. Lancet , 2015.

[19] Kumar K et al Thirthalli J, Zhou L. Traditional, complementary, and alternative medicine approaches to mental health care and psychological wellbeing in India and china. Lancet Psychiatry, 2016.

[20] Dehury RK Samal J. Can the Ayush system be instrumental in achieving universal health coverage in india. Indian J Med Ethics, 2018.

[21] Testa FM D'Souza R Berg AT, Levy SR. Remission of epilepsy after 2 drug failures in children: a prospective study. Ann Neurol, 2009.

[22] Hapke RJ Huttenlocher PR. A follow-up study of intractable seizures in childhood. Ann Neurol, 1990.

[23] Hesdorffer D Hauser WA French JA Callaghan BC, Anand K. Likelihood of seizure remission in an adult population with refractory epilepsy. Ann Neurol, 2007.

[24] Najjar Y Schiller Y. Quantifying the response to antiepileptic drugs: effect of past treatment history. Neurology, 70:54–65,2008.

[25] Noachtar, S., & Peters, A. S. (2009). Semiology of epileptic seizures: a critical review. Epilepsy & Behavior, 15(1), 2-9.

[26] Ulate-Campos, A., Coughlin, F., Gaínza-Lein, M., Fernández, I. S., Pearl, P. L., & Loddenkemper, T. (2016). Automated seizure detection systems and their effectiveness for each type of seizure. Seizure, 40, 88-101.

[27] Schmidhuber, J. (2015). Deep learning in neural networks: An overview. Neural networks, 61, 85-117.

[28] Lopes, A. T., De Aguiar, E., De Souza, A. F., & Oliveira-Santos, T. (2017). Facial expression recognition with convolutional neural networks: coping with few data and the training sample order. Pattern recognition, 61, 610-628.