POTENTIAL USE OF VIRTUAL REALITY IN TELEHEALTH USINGARTIFICIAL INTELLIGENCE

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Abstract— **Healthcare has become important to live a prosperous life. Telehealth and telemedicine technology help patients to get healthy life at their convenient place. It has become easy for doctors, healthcare providers to assess their patients through telehealth technology. Virtual Reality helps us to be active and productive in our day-to- day life. It helps to reduce stress and cure illness by providing a fitness routine that reduces and heals pain. The automation allows the system to operate according to the patient's diagnosis. This system not only is helpful for patients but also for people who want to have a healthy life. It is time-consuming and cost-saving and it can provide efficient features to detect the cause and solution to prevent it. The aim of this paper is to provide healthy life through virtual assessment and recovery through the issues people are facing to remain physically and mentally fit. The integration of VR and AI has the potential to enhance patient experiences, and healthcare outcomes, and increase access to quality healthcare services, particularly in remote or underserved areas.**

Keywords—**Virtual Reality, Telemedicine, Telehealth, Healthcare.**

I. INTRODUCTION

Virtual Reality (VR) makes a significant impact in the field of telehealth by creating immersive and realistic virtual environments that bridge the gap between patients and healthcare providers, regardless of geographical distances. Through VR, patients participate in virtual consultations that simulate face-to-face interactions, enabling more engaging and personalized healthcare experiences.

VR is transforming training and simulation for healthcare professionals, allowing them to practice complex procedures, learn anatomy, and prepare for emergency situations in a safe and controlled environment. VR is also being utilized in therapy, pain management, and physical therapy exercises. VR in telehealth enables remote monitoring and home care, with the integration of wearable devices and sensors that collect patient data.

A Virtual Environment (VE) is an interactive, virtual image display enhanced by special processing and by nonvisual display modalities, such as auditory and haptic, to convince users that they are immersed in a synthetic space [1]. In a different fashion, virtual reality (VR) is an application that lets users navigate and interact with a three-dimensional, computer-generated environment in real-time [2]. Virtual reality is not only a hardware system [3]. But also an emerging technology that changes the way individuals interact with computers. It can be described as "...a fully three-dimensional computer-generated 'world' in which a person can move about and interact as if they actually were in an imaginary place. This is accomplished by totally immersing the person's senses...using a head-mounted display (HMD)" or some other immersive display device, and an interaction device such as a Data Glove or a joystick [4, p. 111]. However, it is the user immersion in a synthetic environment that characterizes VR as being different from interactive computer graphics or multimedia. In fact, the sense of presence in a virtual world elicited by immersive VR technology shows that VR applications may commonly differ fundamentally from those associated with graphics and multimedia systems [5]. Virtual environments provide a unified workspace, which allows almost complete functionality without requiring that all functions to be in the same physical space. According to Ellis [1, p. 17], VEs can be defined "...as interactive, virtual image displays enhanced by special processing and by no visual display modalities, such as auditory and hap tic, to convince users that they are immersed in a synthetic space." Less technically, a virtual world can be described as an application that lets users navigate and interact with a computer-generated 3-D environment in real-time. The system has three major elements: interaction, 3-D graphics, and immersion [2].

Virtual Reality (VR) technology, when combined with Artificial Intelligence(AI), has the potential to change telehealth by providing immersive and personalized experiences for patients and healthcare providers. VR creates a virtual environment that mimics real-life scenarios, allowing remote consultants, surgical training, mental health therapy, fitness sessions, meditation, and much more. AI algorithms enhance these experiences by analyzing patient

data, providing real-time feedback, predicting outcomes as a solution to the problem, predicting outcomes, and personalizing interventions. Through natural language processing, sentiment analysis, and data analytics, AI enables accurate communication, tailored treatment plans, and proactive monitoring. This integration of VR and AI in telehealth empowers patients, improves healthcare outcomes, and increases access to quality care, regardless of geographical barriers. It holds immense promise for transforming the healthcare landscape by delivering innovative and patient-centric telemedicine solutions.

II. PROPOSED ALGORITHM

A. Working of the VR in Telehealth using AI

The device/system operates with wireless connection wifi to communicate with the Health provider. Health provider monitors the patient through virtual assessment. The system processes the information provided by the patient to the healthcare system with the help of machine learning algorithms and Integrating the services. AI provider and Integrating service environments collects the data from the healthcare provider, analyzed it in real-time data analysis using algorithms to develop a model that can eventually automate. The required information is sent to virtual reality for better understandable through image visualization.
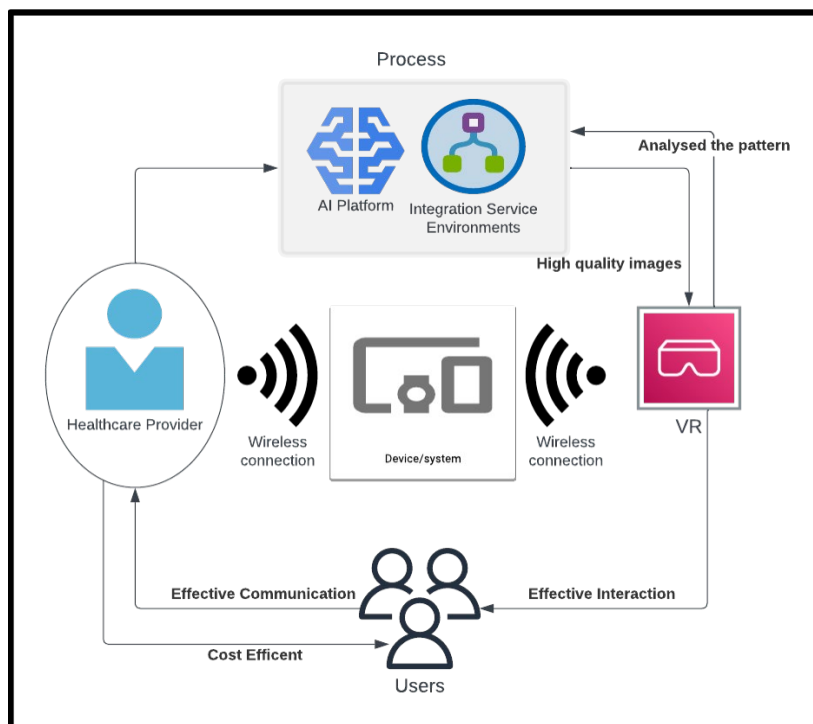

1. Working of VR in telehealth using AI

In the process machine learning develops the images with the help of Gesture recognition, Image and Video Analysis, Virtual Patient Simulation, and Emotional Analysis. Fig.1 shows the overall working of Virtual Reality in Telehealth using Artificial Intelligence. Virtual reality operates its functions to provide effective interaction with the patients/users, it is cost-efficient and helps to provide good communication. The model is further analyzed based on AI algorithms that help to automate through VR to make it interactive for patients' involvement in the recovery of good health.

B. Explanation of Artificial Intelligence in VR

In the Data collection relevant data is collected from various sources, such as patient health records, medical imaging, wearable devices, and virtual interactions. This data forms the foundation for training AI algorithms and creating personalized VR experiences. The collected data undergoes preprocessing and cleaning to ensure its quality and suitability for AI analysis. This may involve tasks such as data normalization, feature extraction, and data augmentation to enhance the dataset. In the next step AI models, such as machine learning algorithms or deep learning neural networks, are developed and trained using the preprocessed data.
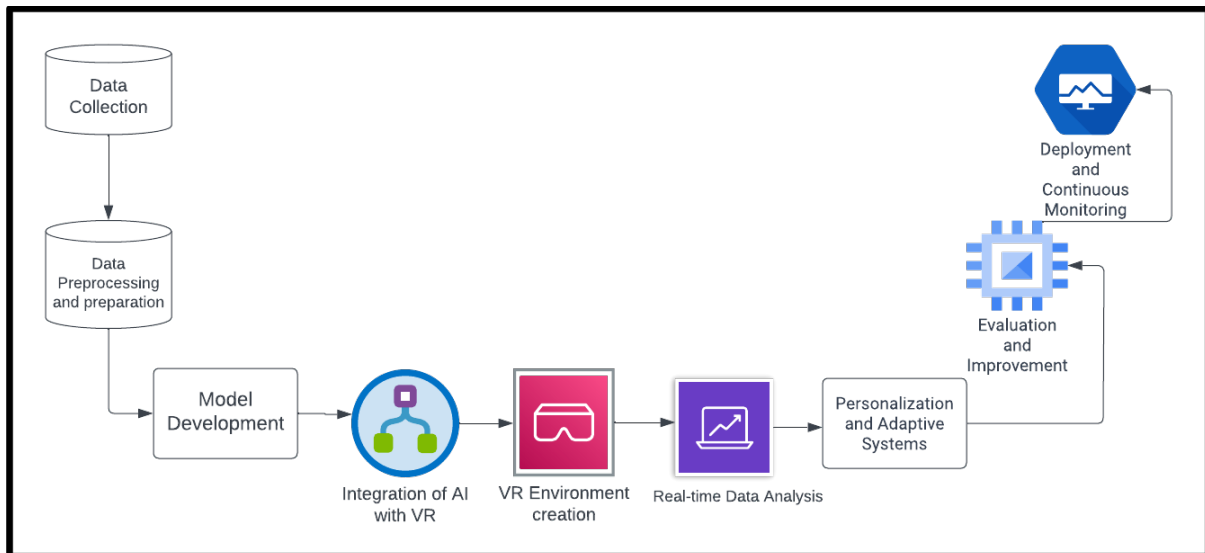
2. Process of Artificial Intelligence in VR

The model is trained to learn patterns, make predictions, classify data, or perform other relevant tasks specific to the telehealth application. Integration of AI algorithms are integrated into the VR telehealth platform. This involves incorporating AI functionalities into the VR software, enabling real-time data analysis, decision-making, or feedback generation within the virtual environment. Virtual environments are designed and developed to simulate various telehealth scenarios, such as virtual consultation rooms, surgical simulations, or therapeutic settings. These environments are tailored to provide an immersive and realistic experience for patients and healthcare providers. During a VR telehealth session, AI algorithms analyze real- time patient data, such as vital signs, movement, or voice data, collected through wearable devices. The algorithms can provide immediate feedback, monitor health parameters, and assist in making informed decisions based on the analyzed data. AI algorithms used in telehealth with the help of VR are as follows- Image and Video Analysis, Natural Language Processing (NLP), Machine Learning for Clinical Decision Support, Gesture Recognition, Virtual Patient Simulation, Emotional Analysis. AI algorithms can adapt and personalize the VR experience based on individual patient needs and preferences. This involves dynamically adjusting virtual environments, therapeutic interventions, or educational content based on patient responses, progress, or health conditions. The AI-driven VR telehealth system is evaluated for its effectiveness, usability, and clinical outcomes.

Response from healthcare professionals and patients is gathered to identify areas of improvement and refine the AI algorithms, VR environments, and overall telehealth experience. AI-driven VR telehealth systems are effective and reliable, and they are deployed for real-world use. Monitoring and maintenance ensure that the system continues to perform optimally, while data from actual usage is used to further refine the AI algorithms and enhance the telehealth platform.

III. EXPERIMENT AND RESULT

The test is set for the evaluation of the result by using machine learning algorithms to test the model.

NER algorithms identify and classify specific entities mentioned in the text, such as medical conditions, medications, procedures, or anatomical terms. NER enables the extraction of relevant information from patient records, medical literature, or online sources. Sentiment analysis algorithms determine the sentiment or emotional tone expressed in text, such as patient feedback, reviews, or social media posts. In telehealth, sentiment analysis helps assess patient satisfaction, detect emotional distress, or evaluate the overall sentiment of conversations between patients and healthcare providers. Text classification algorithms categorize text into predefined classes or categories. In telehealth, these algorithms can be used to classify patient messages or queries into specific topics, triage urgency levels, or route incoming communications to the appropriate healthcare professionals or departments.
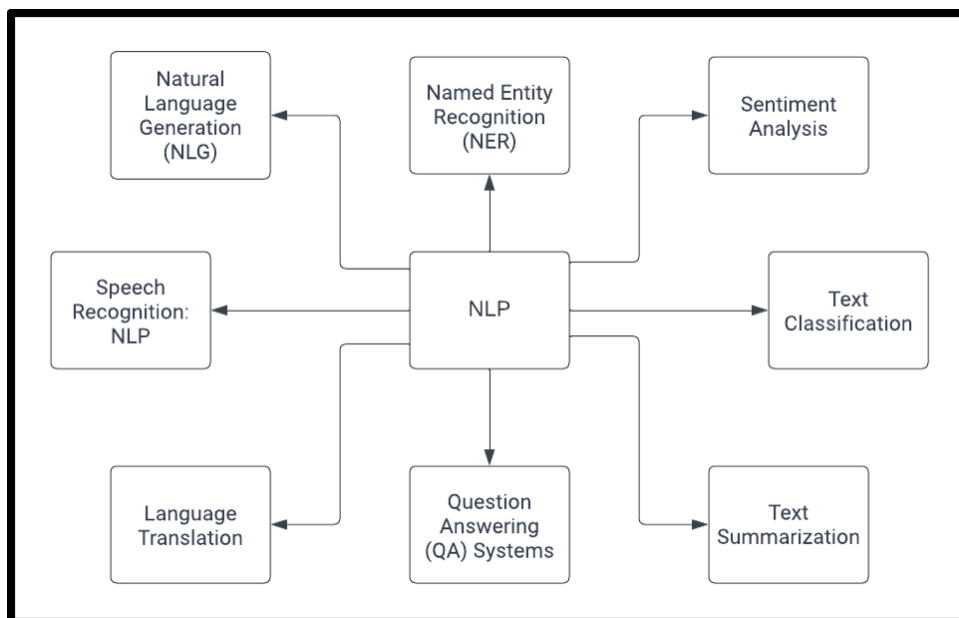
(a)   (b)

Fig 3. Natural Language Processing

Text summarization algorithms condense lengthy texts or documents into shorter, concise summaries. In telehealth, these algorithms can assist in summarizing medical literature, research papers, or patient records, providing healthcare professionals with quick access to essential information. NLP algorithms for machine translation enable real-time translation of text or speech between different languages. In telehealth, language translation algorithms facilitate communication between healthcare providers and patients who do not share a common language, improving accessibility and understanding.

Hidden Markov Model (HMM) in Telehealth provides statistical models that can represent temporal patterns in sequential data, making them well-suited for gesture recognition. HMMs can learn and recognize complex gesture sequences by modeling the temporal dependencies between different poses or gestures.

The Hidden Markov Model (HMM) is an extension of the Markov process used to model phenomena where the states are hidden or latent, but they emit observations. For instance, in a speech recognition system like a speech-to-text converter, the states represent the actual text words to predict, but they are not directly observable (i.e., the states are hidden). Rather, you only observe the speech (audio) signals corresponding to each word and need to deduce the states using the observations. The POS tagging task can be modeled as a Hidden Markov Model with the hidden states representing POS tags that emit observations, i.e., words.
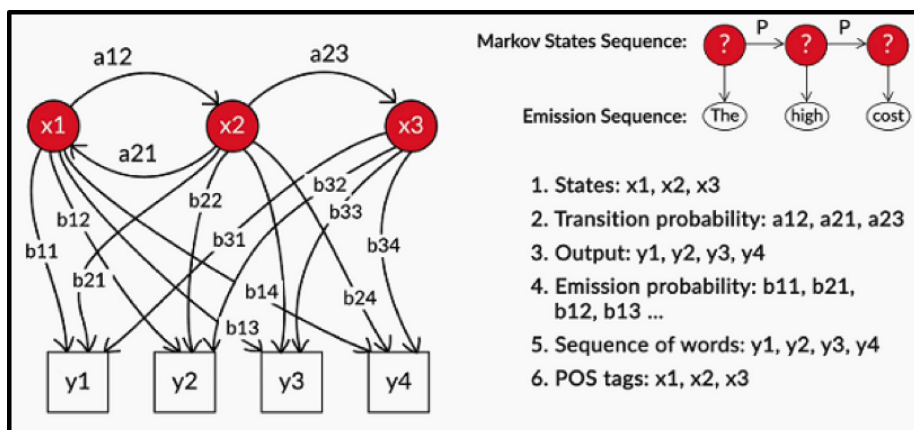

Fig 4. Hidden Markov Model

The hidden states emit observations with a certain probability. Therefore, the Hidden Markov Model has emission probabilities, which represent the probability that a particular state emits a given observation. Along with the transition and initial state probabilities, these emission probabilities are used to model HMMs. The figure below illustrates the emission and transition probabilities for a hidden Markov process with three hidden states and four observations.

CNNs are deep learning models that excel at analyzing visual data, such as images or video frames. In gesture recognition, CNNs can extract spatial features from video frames or depth maps, allowing them to identify and classify different hand or body gestures. RNNs are designed to handle sequential data and are commonly used in gesture recognition tasks. By usingrecurrent connections, RNNs can capture temporal dependencies and learn patterns in time-series data, making them suitable for recognizing dynamic gestures.

Support Vector Machines are supervised learning models that can classify data into different classes based on their features. In gesture recognition, SVMs can learn to differentiate between different gesture patterns by finding an optimal decision boundary in a high-dimensional feature space.
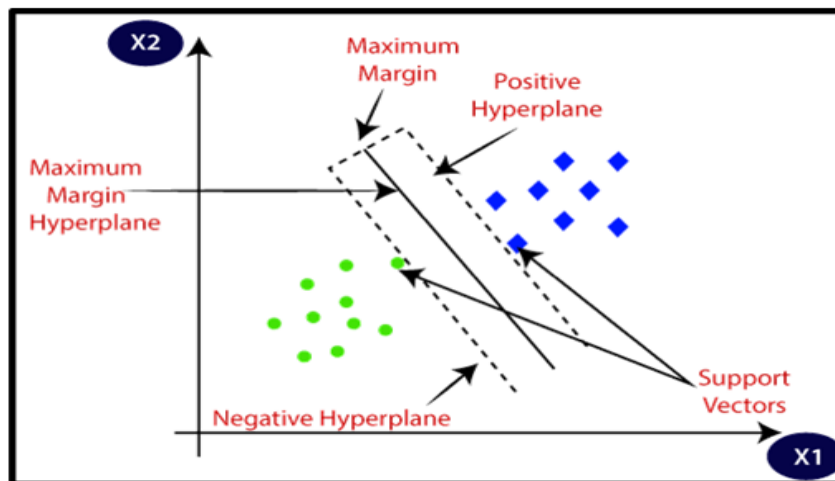

Fig 5. Support Vector Machine

In telehealth, SVM works by analyzing patient data and creating a model that can make predictions or classifications based on that data. To apply SVM in telehealth, the first step is to gather relevant patient data. This may include medical records, diagnostic test results, patient demographics, lifestyle factors, or any other information that is deemed useful for the specific application.
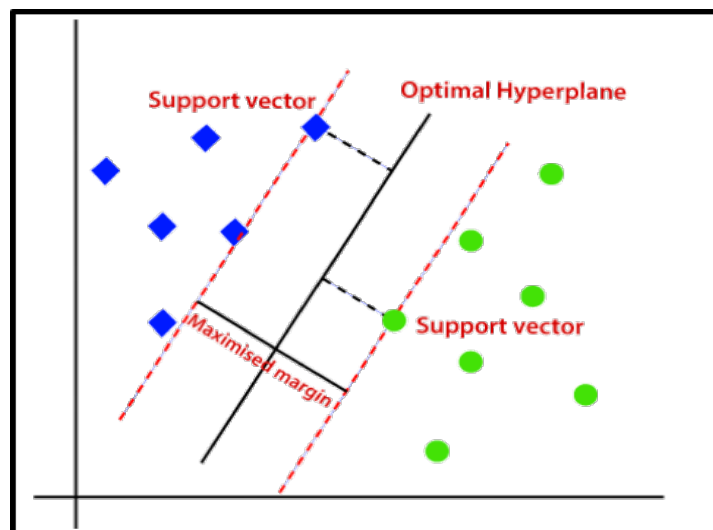

Fig 5.1. Support Vector Machine

Next, the data is preprocessed and transformed into a suitable format for SVM. This typically involves feature extraction or selection, where the most informative features or variables arechosen to represent the patient data. The data may also need tobe normalized or scaled to ensure that all features have equal importance during the SVM training process. As the data is prepared, the SVM algorithm is trained using a labeled dataset. In telehealth, this dataset may consist of patient records with known outcomes or classifications, such as the presence or absence of a certain medical condition or the success or failure of a particular treatment. During the training phase, SVM aims to find an optimal hyperplane that separates the data points into different classes or categories. The hyperplane is positioned to maximize the margin, which is the distance between the hyperplane and the nearest data points from each class. The SVM algorithm seeks to find the hyperplane that achieves the maximum margin while minimizing classification errors. The SVM model is trained, it can be used to make predictions or classifications on new, unseen patient data. The model takesthe features of the new patient data as input and predicts the corresponding outcome or classification based on the learned patterns from the training phase. In telehealth, SVM can be utilized for various tasks, such as disease diagnosis, risk prediction, treatment planning, patient monitoring, adverse event detection, or sentiment analysis. SVM's ability to analyze and classify patient data, healthcare providers can make more accurate predictions, improve decision-making, and enhance patient care in telehealth settings.

Mathematical Intuition behind Support Vector Machine
The dot product can be defined as the projection of one vector along with another, multiplied by the product of another vector.
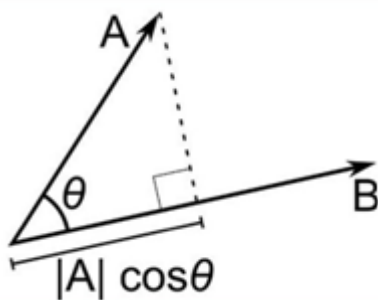
Here a and b are 2 vectors, to find the dot product between these 2 vectors we first find the magnitude of both vectors and to find the magnitude we use the Pythagorean theorem or the distance formula. After finding the magnitude we simply multiply it with the cosine angle between both the vectors. Mathematically it can be written as:
$A . B = |A| \cos\theta * |B|$

Where $|A| \cos\theta$ is the projection of A on B And $|B|$ is the magnitude of vector B

Now in SVM we just need the projection of A not the magnitude of B, I'll tell you why later. To just get the projection we can simply take the unit vector of B because it will be in the direction of B but its magnitude will be 1. Hencenow the equation becomes:
$A.B = |A| \cos\theta *$ unit vector of B

Use of Dot Product in SVM:
Consider a random point X and we want to know whether it lies on the right side of the plane or the left side of the plane (positive or negative).
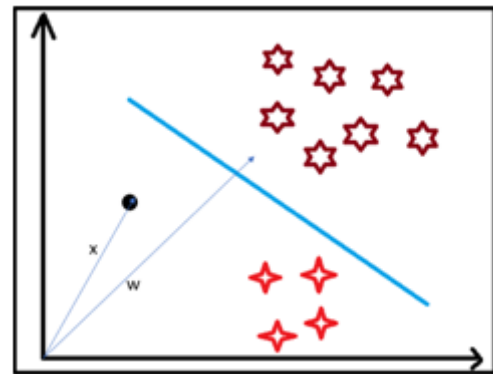

Fig 6. Graph of Support Vector Machine

To find this first we assume this point is a vector (X) and then we make a vector (w) that is perpendicular to the hyper plane. Let's say the distance of vector w from the origin to thedecision boundary is 'c'. Now we take the projection of the X vector on w.
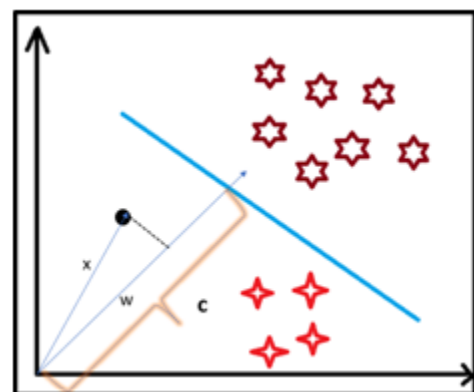

Fig 6.1. Graph of Support Vector Machine

We already know that projection of any vector or another vector is called dot-product. Hence, we take the dot product ofthe x and w vectors. If the dot product is greater than 'c' then we can say that the point lies on the right side. If the

dot product is less than 'c' then the point is on the left side and if the dot product is equal to 'c' then the point lies on the decision boundary.

$$\vec{X}.\vec{w} = c \ \text{(the point lies on the decision boundary)}$$

$$\vec{X}.\vec{w} > c \ \text{(positive samples)}$$

$$\vec{X}.\vec{w} < c \ \text{(negative samples)}$$

Margin in Support Vector Machine

We all know the equation of a hyperplane is w.x+b=0 where wis a vector normal to hyperplane and b is an offset.
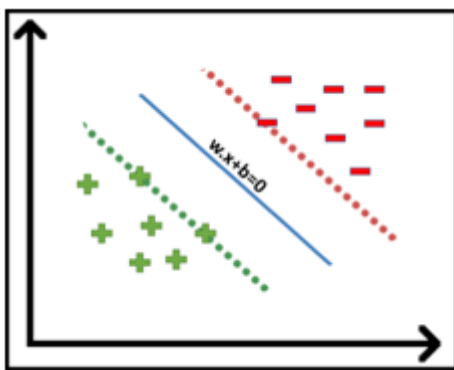

Fig 6.2. Graph of Support Vector Machine

To classify a point as negative or positive we need to define adecision rule. We can define decision rule as:

$$\vec{X}.\vec{w} - c \geq 0$$

$$\text{putting} -c \text{ as b, we get}$$

$$\vec{X}.\vec{w} + b \geq 0$$

hence

$$y = \begin{cases} +1 & \text{if } \vec{X}.\vec{w} + b \geq 0 \\ -1 & \text{if } \vec{X}.\vec{w} + b < 0 \end{cases}$$

If the value of w.x+b>0 then we can say it is a positive point otherwise it is a negative point. Now we need (w,b) such that the margin has a maximum distance. Let's say this distance is'd'.
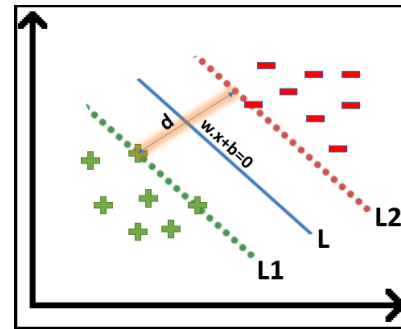

Fig 6.3. Graph of Support Vector Machine

To calculate 'd' we need the equation of L1 and L2. For this, we will take a few assumptions that the equation of L1 is w.x+b=1 and for L2 it is w.x+b=-1.

The decision function for SVM can be defined as follows:
f(x) = sign(w^T * x + b)
In this formula:

- f(x) represents the predicted class or label for the input data point x.
- w is a vector of weights that determines the orientation of the hyperplane.
- b is the bias term that controls the position of the hyperplane.

During the training process, the SVM algorithm seeks to findthe hyperplane that satisfies the following conditions for eachdata point (x_i, y_i):

y_i * (w^T * x_i + b) ≥ 1

Here:

x_i is the input feature vector for data point i.
y_i is the true class or label for data point i, which is either +1or -1, depending on the class.

The above condition ensures that each data point is correctly classified by the hyperplane, with a margin of at least 1 between the hyperplane and the closest data points from eachclass.
Random Forests are an ensemble learning technique that combines multiple decision trees to make predictions. In gesture recognition, random forests can be trained on hand-crafted features extracted from gesture data to classify and recognize different gestures.
Random Forest is an ensemble learning algorithm that combines multiple decision trees to make predictions. The formula for Random Forest involves the aggregation of predictions from individual decision trees.
Given an input data point x, the Random Forest algorithm predicts the target variable y by averaging or voting the predictions from the ensemble of decision trees.

Regression:

For regression tasks, the predicted value y_hat for a given datapoint x can be computed as:

y_hat = (1/N) * Σ(tree_i(x))Here:

N is the total number of decision trees in the Random Forest

ensemble.

tree_i(x) represents the prediction of the i-th decision tree forthe input data point x.

The predicted value y_hat is the average of the predictions from all the decision trees in the Random Forest.
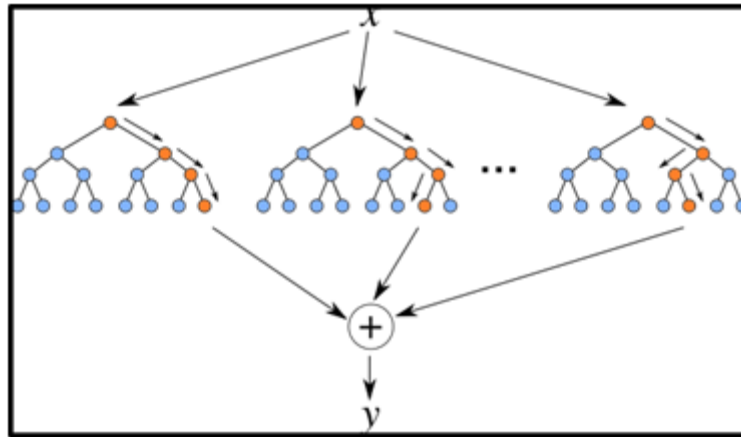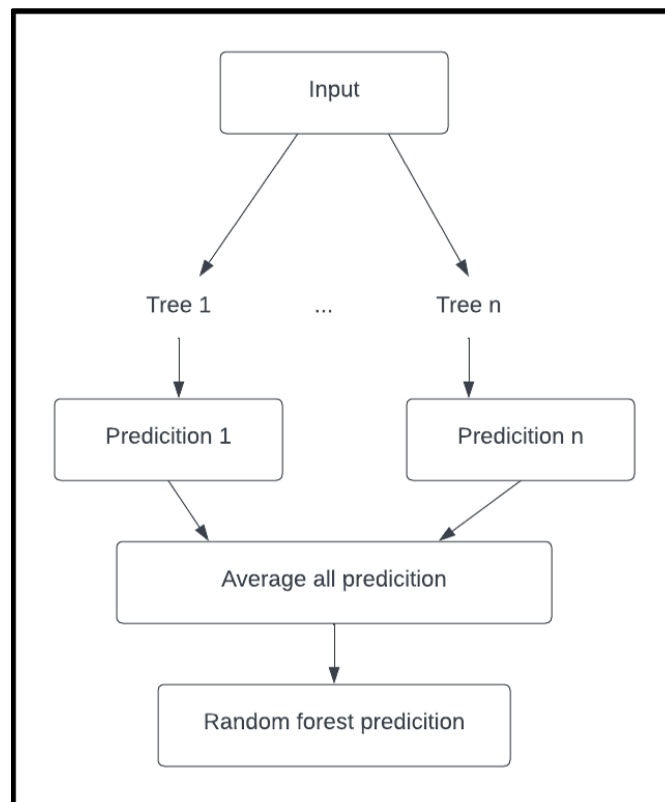

Fig 7. Random Forest Regressor

Fig 7.1. Random Forest

Random Forest uses majority voting for classification tasks todetermine the predicted class label for a given data point x.

y_hat = argmax(Σ(tree_i(x)))Here:

tree_i(x) represents the predicted class label of the i-th decision tree for the input data point x.

argmax returns the class label that appears most frequently inthe ensemble of decision trees.

The predicted class label y_hat is the one that receives the highest number of votes among all the decision trees.
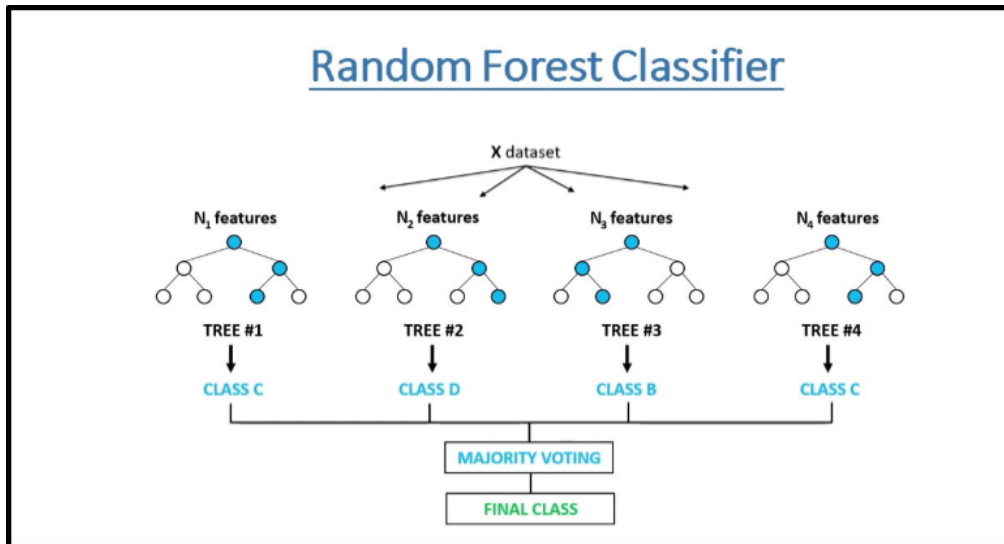

Fig 7.2. Random forest classifier

LSTM is a type of RNN that addresses the vanishing gradient problem and is capable of capturing long-term dependencies in sequential data. LSTMs have been applied successfully in gesture recognition tasks, particularly when dealing with longer and more complex gesture sequences.

GMMs are probabilistic models that can represent the statistical distribution of data. In gesture recognition, GMMs can be trained on extracted features from gesture data and used to classify new gestures based on their likelihoods.

IV. CONCLUSION

This research paper includes all possibilities of aiming for a healthy lifestyle. Technology is growing the ability to develop systems which can be a good investment for the people. In the world of competition it becomes necessary to take care of our health. This paper gives the implementation of a system which will prevent health issues and people can fully concentrate on becoming fit through virtual reality. AI helps to build the system in a more interactive way and can reach areas that are underdeveloped where they can directly contact healthcare providers at low cost and feasible time.

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