GAIT MONITORING BY ANKLE KINEMATICS FOR THE MEDICAL INDUSTRY

Abstract:

There are a lot of people who met with the accident, had bone fractures in their legs, and are struggling to walk properly. Even though there are physiotherapists to help patients in their progress of healing the leg and walking properly but the physiotherapist will be present with the patients only for a few hours. So the patient is unaware of whether the moment that which he made is correct or not. So we have come up with a device that will be placed in the ankle which will help to know whether the patient is properly doing the exercise. The physiotherapist will note the continuous progress/ movement and will take further steps to improvise the time of healing the bone fractures.

Keywords: Gyroscope, First Touch, Last Touch, Mid-swing, Lambda, peaks, valley

1.INTRODUCTION

A leg injury is a type of injury that affects the legs, including the bones, muscles, tendons, and other tissues. Leg injuries can range from minor sprains and strains to serious fractures, dislocations, and ligament tears. Some common causes of leg injuries include falls, sports-related activities, car accidents, and blunt trauma. In terms of symptoms, leg injuries can cause pain, swelling, bruising, and difficulty moving the affected limb. Treatment for a leg injury depends on the severity and type of injury but may include rest, ice, compression, elevation, physical therapy, and in some cases, surgery. It's important to seek prompt medical attention for any leg injury, as delaying treatment can lead to prolonged pain and impaired function. Additionally, some leg injuries, such as fractures, can result in long-term complications if not properly treated.

In order to prevent leg injuries, it's important to engage in regular exercise and stretching to maintain flexibility and strength, wear appropriate protective gear during sports and physical activity, and take steps to reduce the risk of falls, such as removing tripping hazards from the home and workplace. Especially many of them make their femur bone damage which is the strongest bone and this fracture needs a longer time to recover. If no proper recovery it will lead to dissection of the legs. So proper treatment has to be given. It will be very easy for the physiotherapist to teach the exercise and to monitor and they are asked to practice regularly but, in the case, for the patient, it will be difficult for them and their family members difficult to know whether he/she is doing the exercise properly.

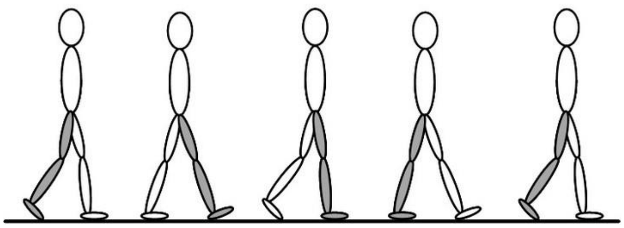


Figure.1

Gait classification is the process of identifying and categorizing different types of human walking patterns based on certain parameters such as speed, stride length, step length, and body posture. This information can be useful in various applications, such as rehabilitation, sports training, and healthcare.

In recent years, the use of Internet of Things (IoT) devices has made it possible to gather data from sensors such as accelerometers, gyroscopes, and magnetometers to classify gait patterns. The collected data is processed and analyzed in real-time to identify specific features of the gait, such as the cadence, swing phase, and stance phase. IoT devices can also provide additional information such as heart rate, body temperature, and muscle activity, which can be used to enhance gait classification accuracy. The use of wearable IoT devices, such as smartwatches and activity trackers, has made gait analysis more accessible and convenient, as these devices can be worn on the body to continuously monitor walking patterns.

Overall, the use of IoT devices in gait classification has the potential to improve rehabilitation and training programs, provide a better understanding of gait patterns, and enable early detection of gait-related disorders. Many scholars use Image processing to detect the movement of the body.[2][7] to detect skeletal movement. Many used the IMU readings to get the Gyroscope values with a hardware setup. Some scholars use mobile phone gyroscope values to detect. But this results in failure because of the cost so that a middle-class family can’t offer a high amount to buy.

So for the best understanding of them, we will be detecting the motion of the ankle with the help of a Gyroscope z-axis value, and with the help of an application the patient will be able to know the proper walking pattern.

2.LITERATURE SURVEY:

[1]In the process of detecting leg motion research by Alexander Turner Et al used F-Scans to diagnose gait abnormalities in patients for clinical purposes. Regardless of any other neuromuscular movement disorders, the patients may have, the motivation behind this method is to diagnose gait abnormalities symptom by symptom.

A deeper understanding of movement disorders may result from this, as well as advancements in treatment. shoe pressure inside was assessed for 12 physically fit subjects who underwent eight artificially induced gait modifications by changing the shoe's underside. The deep learning architecture and long-term short-term memory networks were used to assess the 2520 data channels worth of data that were recorded at 100 Hz. In addition, the basis for these networks' decision-making process was examined. This came out so well as the used Non-invasive methodology and unprocessed dynamic gait data. [2] Kinect Cameras were used in another work by Wei Shao et al where they developed a non-contact, reliable strategy for identifying those at risk of developing depression.

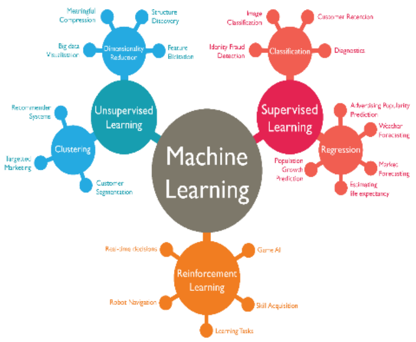


Figure.2

We suggest a multimodal gait analysis-based depression identification method that combines skeleton modality and silhouette modality to increase the accuracy and practicality of depression detection. In order to execute the sequence strategy, we first present a skeleton feature set to define depression and train an LSTM model. Second, we create two Convolutional Neural Network (CNN) models with a unique loss function to extract silhouette features from front and side viewpoints from RGB films using Gait Energy Image (GEI) as silhouette features. According to the experimental findings, the suggested strategy leveraging complementarity increased accuracy while minimizing gender discrepancies which makes it more effective and convenient.

[3]The work of Suil Jeon et al came up with a clinical solution for the treatment and diagnosis of gait-related diseases. The goal of this study was to build a machine-learning technique for automatically categorizing five anomalous gait traits from three-dimensional gait kinematics data, including toe-out, genu varum, pes planus, hindfoot valgus, and forward head posture features. We gathered 488 subjects' gait data and labelled their gait features. Using a variational autoencoder, the orientations of the human body's various body parts during a gait cycle were translated to a low-dimensional latent gait vector. Five gait features were classified by a two-layer neural network using logistic regression, and an abnormal gait feature vector was produced (AGFV). When the AGFV was rounded to the closest zero or one, the proposed network demonstrated balanced accuracies of 82.8% for toe-out, 85.9% for hindfoot valgus, 80.2% for pes planus, 73.2% for genu varum, and 92.9% for forward head posture. The suggested method has a practical benefit over existing gait indices, such as the gait deviation index with a single value, in that it can identify many aberrant gait aspects as opposed to just one. The overall findings supported the viability of applying the suggested technique to identify individuals with anomalous gait characteristics using three-dimensional motion capture data. The five different forms of anomalous gait features were found using a cycle of gait kinematics data, and the suggested network demonstrated a pretty high level of accuracy and outperformed a previous method in doing so.

[4]As A alternative to the cameras, the Inertial sensors containing a triaxial accelerometer, gyroscope, and magnetometer were used in the work of Jinwon Lee for the seamless control of the lower-limb robotic assistive devices (e.g., exoskeletons or prostheses) during ambulation. Several studies have attempted to quantify the gait phase utilizing a thigh or shank angle in order to accomplish this. However, their estimation varied across walking speeds and produced some variation from the real walking. In this study, we looked at various machine-learning settings to estimate the gait phase of a robotic transfemoral prosthesis more precisely and consistently over a range of walking speeds. They presented two distinct sensor configurations with the transfemoral prosthesis use in mind and experimentally tested them on three healthy participants. The findings demonstrated reliable estimates regardless of walking speed. However, depending on the design, there were minor variations in the ease of the sensor setup and the precision of the estimation. S2 had the advantage of calculating heel strikes more accurately than S1 by using additional heel force data, while S1 had the advantage of a straightforward equipment setup with only two IMUs. The decision between the two sensor setups for the gait phase estimation in prosthesis application is thus how we would begin our conclusion. In consideration of the device design or the

research objective, the researchers can select the ideal sensor setup.

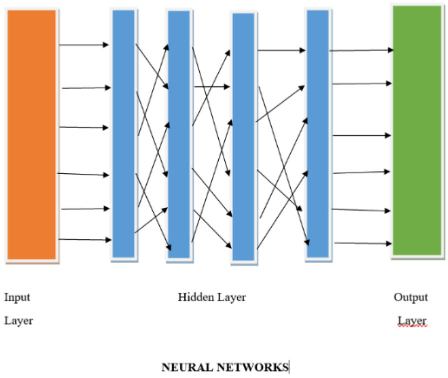


Figure.3

[5] The work of Lei Wang was useful for clinical gait evaluation in patients. Many clinical investigations have adopted inertial measuring units (IMU) for gait analysis as a more practical, affordable, and unrestricted substitute for the instrumented pathways or motion-capturing systems for laboratories. These studies frequently used spatial-temporal gait metrics such as stride length and gait cycle time computed from the IMUs to assess the altered gait. However, the spatial-temporal data offered by IMUs is constrained and is evaluated inadvertently or ineffectively. In this paper, we create a brand-new IMU-based approach for assessing clinical gait. Two shank-mounted IMUs are used to extract nine gait variables, including three spatial-temporal parameters and six kinematic parameters, to measure patient gait abnormalities. An IMU-based gait normality index (INI), which is derived from those characteristics, is used to assess the overall gait performance. Ten healthy participants and eight inpatient patients with n-hexane neuropathy-related gait deficits were enrolled. Throughout the rehabilitation procedure and until discharge, the hypothesized gait variables and INI were assessed on the inpatients every three to five-time points. The proposed new set of gait variables and INI can provide adequate and effective information for quantifying gait abnormalities, and help understand the progress of gait and effectiveness of therapy during the rehabilitation process, according to a comparison with healthy subjects and statistical analysis for the changes of gait variables and INI.

[6] Elliott Fullerton et al researched human activity recognition using IMU sensors. This investigation can learn a lot about a patient's behavior by recognizing human activity, which can also help with future recommendations for prescribing activities. Body-worn accelerometers have been shown to be a reliable way to monitor human activity, although it is unclear what kind of study has been done on its application in free-living situations to identify a variety of activities. In this study, numerous body-worn accelerometers were used to identify activity and subcategory activity kinds in a free-living environment. Nine body-mounted accelerometers were worn by ten subjects for a day of independent living (age = 23.1 1.7 years, height = 171.0 4.7 cm, and mass = 78.2 12.5 Kg). A range of machine learning methods, including feature and classifier selection, pre-processing algorithms, and accuracy testing, were evaluated. With unfiltered mean and standard deviation variables, a fine k-nearest neighbor classifier showed a recognition accuracy of 97.6%. The recognition of subcategory activities was carried out with great accuracy (>95.0%) in controlled and free-living testing. Maximum features and decision tree classifiers were shown to have the fastest computation times. Results demonstrate that numerous body-worn accelerometers can be used to identify activity and sub-category activity kinds in a free-living environment. With the use of this technique, recommendations for periods of

exercise and inactivity can be made for healthy living.

[7] Gait problems are widespread in the elderly, substantially impair patients' movement, and occasionally signal catastrophic neurological conditions at the root of the condition. It would be ideal if gait issues could be automatically and quickly diagnosed. Patients must bear burdens as a result of current wearable gadget technologies. We develop SAIL, a video-based technology, to carry out contactless gait analysis automatically. The skeleton detector, parameter extractor, and gait classifier are the three components that make up the SAIL. The skeleton detector transforms RGB films into a human skeleton sequence by means of a posture estimation algorithm. Then, using a signal detection technique, the parameter extractor collects gait parameters from skeletons. In order to identify abnormal gait, a trained Support vector machine is utilized as a gait classifier. On our SAIL-TUG dataset, the SAIL outperforms general clinic doctors with 86.2% sensitivity and 98.5% specificity for the detection of aberrant gait, scoring 76.4% and 97.4%, respectively. The final gait report contains nine gait metrics as well as the binary gait classification result. We deploy the user-interface software for our automatic gait assessment system, which is based on SAIL, in more than 60 hospitals for real-world use. Over 30 000 gait reports have been created automatically. Additionally, we create the SAIL-TUG dataset, a freely accessible collection of 404 Timed "Up & Go" films with annotations

3. METHODS

We have been using and comparing with 5-6 algorithms which will help us to get a wide idea of all the algorithm techniques which include Machine Learning, Deep Learning, and other techniques.

a)Decision Tree

It’s a supervised type of learning where it tells if this is the case then what will be the output for this case? It consisted of root, branch, and leaves layer The main terms that have to be found is the Information Gain and Entropy Gain. The attribute which has the highest Information Gain will act as the root node and will be subdivided into branches and the final output which is what we are going to do will be present in the leaves node. In programming first, we will be getting the dataset and will be splitting the data for training and testing.

b)Random Forest

A random forest is nothing but it is almost like the Decision tree. In simple, we can say that A collection of Decision Tree is the Random Forest. It will work based on a Random feature which is Random Bagging. This will help us to decrease the value of co-relation between the Decision-tree. In programming, it’s the same procedure as the decision tree.

c) KNN

It is known as the K-Nearest neighbor. It belongs to Unsupervised learning where the output does not contain any class label. The result will be calculated based on the points which are close to each other. To find the distance we can use the formula Euclidean Distance as well as Manhattan Distance. This will make to

Reference Papers	Author	Objective	Algorithms	Hardware	Advantages	Dataset	Participants
The Classification of Minor Gait Alterations Using Wearable Sensors and Deep Learning	Alexander Turner Et al	Diagnosing gait abnormalities in patients	LSTM and CNN	F-Scan	Non-invasive methodology and unprocessed dynamic gait data	Live Data (Tekscan, Boston, USA)	12
A Multi-Modal Gait Analysis-Based Detection System of the Risk of Depression	Wei Shao et al	Detecting people at risk of depression	CNN and LSTM	Kinect cameras	More effective and convenient	Live Data (Institutional Review Board of Lanzhou University) -Skeleton and RGB dataset	200
Anomalous Gait Feature Classification From 3-D Motion Capture Data	Suil Jeon et al	Detecting anomalous gait features aids in the diagnosis and treatment of gait-related diseases	FNN	Camera	Relatively high accuracy highly practical for clinical applications	Live Data (Motion Analysis Co., Santa Rosa, California)	500
Continuous Gait Phase Estimation Using LSTM for Robotic Transfemoral Prosthesis Across Walking Speeds	Jinwon Lee et al	User gait phase estimation for lower-limb robotic assistive devices	LSTM	Two 9-axis IMUs	S1-more accurate heel-strikes S2-additional heel force data	Live Data (BeagleBone Black, Texas Instruments, USA)	-
IMU-Based Gait Normalcy Index Calculation for Clinical Evaluation of Impaired Gait	Lei Wang et al	Clinical gait evaluation	Gait Variable Selection and Estimation	Two IMUs (InvenSense MPU-6050)	Great potential in the evaluation of other kinds of impaired gait	Offline Data (Sd Card)	-
Recognizing Human Activity in Free-Living Using Multiple Body-Worn Accelerometers	Elliott Fullerton et al	Recognizing human activity	Decision tree classifiers, Support vector machines Nearest Neighbour methods	Inertial sensors containing a tri-axial accelerometer	Pre-processing algorithms had no aid on recognition accuracy	Recorded Data	10
SAIL: A Deep-Learning-Based System for Automatic Gait Assessment From TUG Videos	Yanhong Wang et al	perform clinic-level diagnosis without any wearable devices and professional doctors	SAIL(skeleton detector, parameter extractor, and gait classifier)	Astra camera	Clinic-level diagnosis without any wearable devices and professional doctors	SAIL-TUG (Recorded Videos)	-

TABLE.1

cluster the points based on the closest distance without the term of class label. In programming again we will be getting the data as input and splitting the data as training and testing and then we will predict the output.

d)Naïve Bayes

It is another method of classification. This is all based on the concept of probability. The value will be taken for the hypothesis for the possible value of being true or false. It is all based on the likeness with the true evidence value. Again, here the value is being split into training and testing datasets to derive the output for the programming

e) LSTM

Here we are entering into the concept of Deep Learning which includes the concept of neural networks. It almost acts like a human neural system. Here the LSTM is called the Long-Short Term Memory. It will act as a concept of storing and remembering the data. In other words, we can say it is the Recurrent Neural Network. In programming, we will be creating numerous layers by adding various activation functions we will be setting random state values. We will be getting output in the output layer.

f) Event Detection Method

In this method, we will be using algorithms. At first, we will be checking whether the event had occurred or not, and in the 2 algorithms, we will be classifying the event. We will be using the gyroscope values of the z-axis and we will be using it to classify the different states like First-touch, Last-touch, Mid-Swing, and Lambda values. These values are nothing but the value based on the position of the leg. Finally, the values of peaks and valleys are to be calculated and then with that, we will be able to get the above 4 values that we mentioned. With the help of some logic, we will be getting what the Event had done.

4)HARDWARE SETUP

Here the main components we are using here are the Node MCU and MPU-9250 sensor.

a)Node MCU

Figure.4

It's mainly made for the ESP8266 WIFI module. This will almost be like that of Arduino It will be having 11 digital pins and analog pins. It will work on an operating voltage of 3.3V and with an input voltage of 5V. It has a GPIO pin which helps us in operating the sensors by making it LOW or HIGH. In our case, it's about controlling the MCU-9250 sensor. It can be connected with the help of TX and RX pins

b)Lithium Battery

Figure.5

We will be using the 3800-mAh Battery for the power supply that will be connected with the Node-MCU and it will get an input voltage of about 5V which help us to make the MPU-9250 sensor work.

c)MPU-9250

Figure.6

It's an accelerometer and gyroscope sensor which help us to identify 3-axis accelerometer values,3-axis magnetometer, and 3-axis gyroscope values it will help us to get the required gyroscope z-axis values The operating values should be in the range of 2.4V to 3.6V. The value will be measured and transferred to the Node-MCU with the help of TX and RX ports.

Figure.7

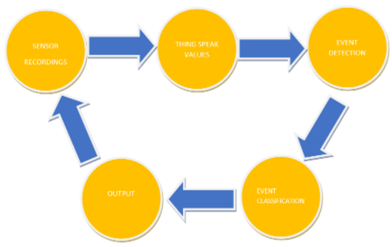
In addition to that, we will be having a small ankle bag that is tied at the ankle that withholds the hardware setup and helps to transfer the data.

5)ALGORITHMS

We are going to discuss the Event Classification Algorithm here in detail. We will be having two algorithms. One is the Event Detection and the other is the Event Classification.

a)Event Detection

In this algorithm, we will be detecting the event first we will be reading the values of gyroscope sensors from both legs and we will be combining the values of 2 legs after 2 values alternatively to mark the movement of two legs. Then with that combined list, we will be finding the peak values and the value of the valley separately with the help of a separate function. and then we will be combing the peak and the valleys list. And then the calibration value of the MPU-9250 sensor has to be calculated and then Algorithm-1 has to be implemented.



BLOCK DIAGRAM

Figure.8

b)Event Classification

In this algorithm, we will be classifying the events based on the values that we found as FC, LC, Lambda and MS. By applying the algorithm-2 We will be getting the output value

6)EXPERIMENTAL SETUP

We will be making two different setups for each leg. This means that we will be having two different Node MCU, MPU-9250 and 3800-mAh per leg. So we will be placing it near the ankle of each leg. That will be helping us in measuring the Gyroscope z-axis values. The Connection for the setup between Node-MCU and MPU-9250 goes as follows.

Algorithm-1(Event Detection)

C=20 ← **Sensor Calibrated Values**

cfc,i,fc,lam,lc,msc=0

m[1:n] ← **Gyroscope z values**

for (1……n)

if(C-(m[i]+m[i-1])>0

cfc++

if(cfc= =2) then

FC detected

cfc=0

if((C1*m[i]<=m[i]<=C) and (fc!=0)) then

lam detected

if((m[i+1]<=C2)and (lam!=0)) then

lc detected

if((m[i+2]>0)and(lc!=0)) then

msc detected

else

i=i+3

else

i=i+2

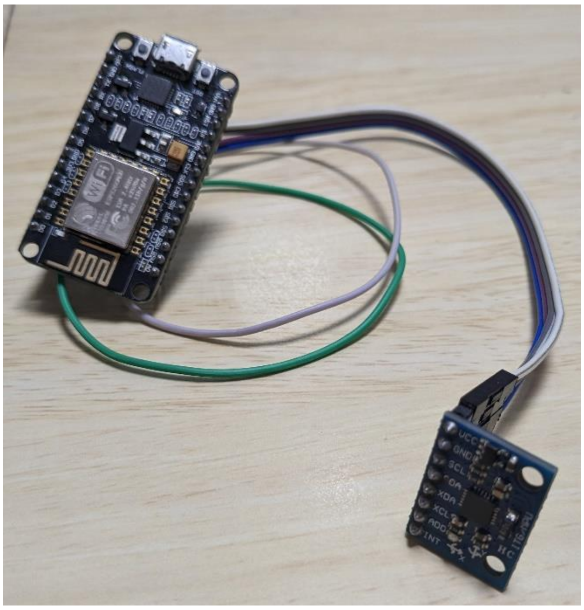


Figure.9

The Ground of the Node-MCU is being connected to the Ground of MPU-9250 and the 3V in Node-MCU is being connected to the Vin in MPU-9250. SCL and SDA will be connected to the 2 digital pins in Node-MCU. This can be made to work in 2 ways one we can connect the USB cable to the system in order to make that work but in our case, since we are using it as WIFI we can connect a lithium battery to this setup just by connecting the ground and Vin in the NodeMCU.

a)Arduino IDE

In Arduino IDE we will be writing the codes that help in the connection of the hardware circuit. We will be setting the pins where we are getting the inputs and will compile and upload it to the NodeMCU and then we will retrieve the value from MPU-9250 to NodeMCU and then back to Arduino IDE.

Algorithm-2(Event Classification)

```
C2=3
Result= [‘ONGROUND’]for(1.2.3…..n)
  if(lad[i]!=0)
    if(lad[i]>0)
         result=[‘WALKING UPSTAIRS’]
    if(lad[i]>lam)
        result=[‘WALKING DOWNSTAIRS’]
    if((cd[i]>alpha)and(result[i-1]!="WALKING IN TREADMILL"))
        result=[‘ TRANSITION STATE’]
    if((cd[i]>alpha)and(result[i-1]!="WALKING UPSTAIRS")or(result[i-1]!="WALKING DOWNSTAIRS"))
         result=[‘ WALKING IN TREADMILL’]
    if(cd[i]<=alpha):
       result=[‘ ON GROUND’]
  if(dif<C2):
   result=[‘ STATIONARY’]
```

b)ThingSpeaks

In this, the code will be written in the Arduino IDE and will get the values and plot the graph. This will also help us to maintain the records of all the values and will also help us in importing the values.

c)Python IDE

In Python IDE we will be executing the codes of Decision Tree, Random Forest, KNN, Naïve Bayes, and LSTM code. We will be executing the code and the output will be displayed. In addition to that, a website application will be designed based on the requirements using Python Flask.

d)Jupyter Notebook

In the Jupyter Notebook, we would be executing the codes for Event Detection and Event Classification. We should be adding the dataset file. All should be placed in the same folder so that we can able to insert the data into the code.

7)RESULTS

Various method has been executed and the output has been found by running through various IDE like Arduino, Python, and Jupyter Notebook. We have found the accuracy for the Naïve Bayes, Decision Tree, KNN, Random Forest, and LSTM. The accuracy has been mentioned in Table 2.

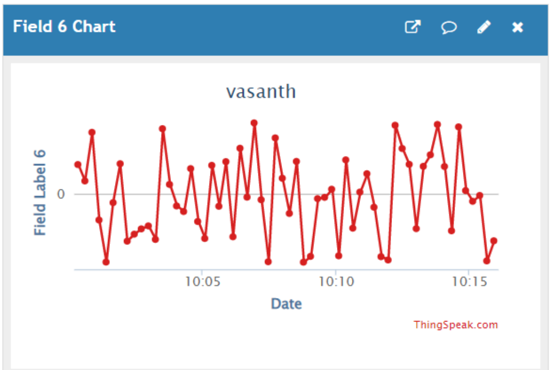


Figure 10

The algorithm we had made for the Event Detection and Event Classification had been made successful and now we can use that as a commercial product that will help patients with quick healing.

Algorithm	**Accuracy in%**
Naïve Bayes	63
Decision Tree	94
K- Nearest Neighbor	92
Random Forest	84
LSTM	44

TABLE.2

8) CONCLUSION

We have implement various machine learning and deep learning techniques and out of that we got the best accuracy for the Decision Tree which is 94 percent. But since it is difficult and it is not on live time basis we are implementing an event detection and classification algorithm to work on the live timing and the patients can able to know the status in instant manner.

9) REFERENCE

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