International Journal of Advances in Engineering and Management (IJAEM)
Volume 8, Issue 5 May. 2026, pp: 130-136 www.ijaem.net ISSN: 2395-5252

MediTrack AI: An Intelligent AI-Based Healthcare Monitoring and Tracking System

Karthik V Nambiar, Robin Negi, Roshan Thomas, Rupashi Bisht, Ram Gopal Sharma
Department of Computer Science and Engineering -AIML
Dronacharya Group of Institutions Greater Noida,U.P., India-201306

Date of Submission: 27-04-2026 Date of Acceptance: 05-05-2026

Abstract*—Healthcare monitor system is important for patients for treatment at correct time. In earlier times, there was way to monitor the patient to watch other people and note it for data from time to time. It may risk health problem that times because it cannot found what is health issue. So the paper talks about how the Meditrack Ai works. Meditrack Ai can help us to watch the patients health data and track patient's health. Meditrack Ai help us to train to find the past mistakes and train the computer to fix the patterns in the health data and there are problems in future. The system is design to doctors and nurses to take care patients by using Meditrack Ai to check the health data and to find health problems early. There will be doctors who alert or reminders to patient like emergency situations. So Meditrack Ai shows that how the system helps to patients care better and helping keep checking on healthcare.

***Keywords*— MediTrack AI, Healthcare Monitoring, Machine Learning, Artificial Intelligence, Patient Health Tracking, Medical Data Analysis**

I. INTRODUCTION

It's clear that healthcare systems, whether in growing nations or established nations, are really struggling. This is because populations are getting bigger, people are living longer, and we're seeing more and more illnesses and conditions linked to our everyday habits. Hospitals and other places that provide healthcare are always under pressure. They've got to give good, fast medical care, but they're stuck with not having enough doctors, nurses and staff, old buildings, and very tight budgets. Seeing how a patient's health changes all the time is really important these days. It helps us catch medical problems very early and stop serious health issues before they even start. It means fewer illness, treatments that actually work, and very few people dying from these illnesses. When we're slow to catch things, illnesses can get very worse, treatments will be costly, and people end up staying more in the hospital for longer and doesn't having a proper treatment. It will be a great help to emergency departments if good monitoring systems are used. They let us focus on preventing these problems rather than just reacting to them. By catching these issues early and keeping a close eye on health and wellness means patients are safe, care is better, and we make good use of what we have in healthcare

When we are keeping an eye on someone's health very often, it means it will contain a lot of manual checks and very occasional visits of doctors and then waiting for the data of the patient to be looked at every time. And when we are doing these things, it means it might miss when a patient starts getting worse, either quickly or very slowly, especially if they need to be watched all the time, all along. So people are really looking for systems that are smart enough to help the doctors, nurses to keep a better eye on the patients, thus making things more accurate and way smoother to be handled.

Digital Healthcare has been very amazing to watch. With this new technology, Collecting lot of patients' information have become possible. We get this information from like smart watches, small sensor, and even our digital health record. Getting a raw medical information can be confuse. "It's kind of hard, do not think?" There is so much information out and even when you look at all regular number. It doesn't really help ypu get proper feel for "what is going on". If we do not have good ways to work with our data and really inside it . We might easily missed out on some truly usefull stuff for patient's care.

Everyone is chatting about Artificial Intelligence and machine learning in medicine, and that is because they are really good at shifting through bunch of information to find that"what is important". Machine Learning systems have shown some real success.When it comes to things like predicting diseases, checking how much risk a patient might be, and helping with clinical decisions.

International Journal of Advances in Engineering and Management (IJAEM)
Volume 8, Issue 5 May. 2026, pp: 130-136 www.ijaem.net ISSN: 2395-5252

These ways of doing things that really make diagnoses much good. They learn from all the past information and can actually adjust as new details come.

Healthcare systems are basically divided into two categories, one which are very old school and one which are very smart, because every time a doctor wants to check the data of a patient, he or she has to look it all by hand, because these systems just don't give any detail which is enough or any information when a patient's health is very rapidly changing. Instead, the systems which are very smart uses AI and machine learning to constantly check the data of the patient and thus finding some important patterns. These systems give early warnings for any kind of problems happening with the patients to the doctors, thus helping the doctors make some good decisions. AI monitoring is way better than the old school method, thus giving us better accuracy and quicker responses and providing more reliability. Smart monitoring is basically a game changer for healthcare because it gives some awesome real-time data and can predict what's next, what's going to happen. That really helps the patients also and makes things run much smoother.

Here also we have looked upon to a bunch of machine learning methods for the health data like decision trees, support vector machines, and logistic regression. And also, some ensemble learning methods were also explored. To improve how good actually a model is, we need to pick out very important features from the medical data. And picking the right features can make a very big difference in both helping the computers working less and making our predictions far much better for the future use.

Basically, it's very important to figure out how to use these algorithms and AI for a better prediction of the health because AI has been doing a lot in the healthcare sector, but we still have a few big problems to figure out. Like, if there is any unstructured information or if there is not enough good examples to be used, then they are all useless data and it also messes the performance of machine learning algorithms. And it makes so tough for these systems to be reliable when we are especially using them in a real-world healthcare. And this also makes these systems very less trustworthy in the real-world situations that haven't been tested yet. Also, if we are using in brand new situations, it also impacts how much we can trust them because a lot of the systems which are out there aren't just built to grow and they can't handle real-time stuff also.

The main problem of great healthcare monitoring is that it is hard to make sense of information, and it also does not align well with the mindset of doctors and nurses. Medical tools usually lack systems that are clear, dependable, and simple to fit into their current routines. So we need a smart system that can predict things well in a simple and understandable manner.

Researchers are trying and actively finding out new methods so that they can monitor health problems. And advanced hybrid AI systems have been created so that they can process data and learn from it to provide real-time information. These platforms help us to reduce paperwork and detect any medical condition earlier while giving clinicians a complete understanding and improving better decision-making through automated prompts when they identifying a connection clearly overall in real practice situation.

So, this paper talks about something called MediTrack AI. It's a smart system for keeping tabs on people's health that uses machine learning to constantly look at their health info. This system helps doctors spot problems early and make better choices about patient care.

II. PROPOSED METHODOLOGY

In Meditrack Ai system, we talks about keep checking on patient’s health data everytime. It can use machine learning to inside the information and detect it. We are trying find out the health issues later. To do that, We have a way of collecting, cleaning up, looking at data that helps us take these problems first. We have to collect the patient’s details from all kind of some systems like sensor type watches, other device instruments, and their’s doctor notes. It includes number like blood pressure ,heart rate, body temperature and oxygen levels. Healthcare data, in its raw form, is often abnormal and has many lots of errors, making a difficult to use analysis right now.

We neat and clean up all the information so we get excellent and always makes detect it. Noise reduction fixes issued caused by very poor sensor or outside interface. We make sure all health data are stable. This way, every piece of information plays proper When we are training machine learning model. We got some gaping the data, so we have to fill in smart math to make result so it will be proper and don’t lose important information. Additionally, we can eliminate useless or poor data points to ensure your information is well-ordered and correct. So, we can check basic to sure number we get that “What’s considered normal for the body”. We took lots of steps before support data into machine learning. It makes dataset more sure and helps models works better and more accurately.

International Journal of Advances in Engineering and Management (IJAEM)
Volume 8, Issue 5 May. 2026, pp: 130-136 www.ijaem.net ISSN: 2395-5252

Once we clean up data, we take out key parts to make it small and faster for computer to work it. We have to teach the computer using old patient data to study about health pattern. It helps to find it's normal or not. These models continuously check new data for any wrong that means it will be risk of health data.

Finally, the system also use adaptive thresholds and look uncommon data points, which it can help us make choices right now. When things got any wrong , it may get any warning and alert pass to healthcare professionals. This offers connection and send clear information to everybody. We put result and current into easy interface that doctors could make quickly and good decisions. So, How Meditrack Ai brings together by giving smart way to keep eye on patient's healthcare.

III. ALGORITHM: ADAPTIVETHRESHOLD

Step1:Input patient health dataset
Step2: Compute observation window size
Step3:The threshold is calculated using the local mean of recent health measurements.
Step4:Classify that blood pressure reading is normal if it's in the right range, if not, it's abnormal.
Step5:Remove short-term noise and unstable readings
Step 6: Let's just get rid of any little differences that are too small to matter.
Step7:Confirm anomalies and generate alerts
Noticing something unusual requires evaluating if your recent health metric varies considerably from your normal data. In adaptive learning, we see an outlier as a data point that stands out big-time. We figure out how far each new health record is from the usual recent readings. Then, we check that against an adaptive limit.
An anomaly is detected when the deviation exceeds the defined threshold value. The proposed methodological workflow is illustrated in **Fig. 1**.

Fig. 1.Diagrammatic illustration of the suggested approach

Adaptive thresholding helps classify patient data as normal or abnormal. We figure out the right threshold for each health thing using recent info.We look at the regular and how much different patient's data changes around it. This helps set a personal limits, not just "one size fits rule". We have added a risky determinant to allow system to adjust to appearing health pattern with very good speed.

The sensitive value, between 0 or 1, helps us stability how quickly the monitoring system behave with how stable with it. Being more sensitive can be good things as it helps you observe it. With less sensitivity, you will not mind it by small stuff , it doesn't matter. When your health numbers be more than the look for, it's real warning sign. You need talk to doctor for this conditions.

Next, We will try out different ways to classify the data methods like Logistics regression, random forest, naïve bayers, support vector machine and xgboost. Xgboost is like decision trees works like a team. Deep learning manages not organize input skilfully. However, in the case of clean healthcare information, tree based model make good connections. XGboost make powerful tool because it developing on regular gradient boosting by using clever building and keeping things stable with regularization. This makes is good for tasks like figure out patient's health data is off.

IV. RESULTS AND DISCUSSION

We have applied five distinct classification approaches: naïve bayes, logistic regression, (SVM)support vector machine, random forest and extreme gradient boosting. We have run all these on the features from our adaptive threshold method to see how do they work . We use the stratified five-fold cross-validation. This means we have split the data into a fair training and testing groups for the evaluation. We need to figure out which approach has best spots unhealthy patients early by checking their health numbers. Early detection of the disease helps the doctors to respond quickly, keep an closer eye on you, which stops the major issues in the future. Below is a table that displays the analysis' findings. These gene biomarkers have previously been connected to the development of the breast cancer.

International Journal of Advances in Engineering and Management (IJAEM)
Volume 8, Issue 5 May. 2026, pp: 130-136 www.ijaem.net ISSN: 2395-5252

TABLEI. PERFORMANCE EVALUATION VALUES

Performance analysis	NB	SVM	LR	RF	XGBoost
✓ Accuracy	86.3184	89.5436	92.6586	97.3711	99.7797
✓ Error	5.6816	4.9959	4.5734	4.0217	3.7453
✓ Sensitivity	99.9999	99.8731	99.4643	99.2754	98.3871
✓ Specificity	34.2105	40.4853	46.2795	57.4211	68.4211
✓ Precision	95.2015	95.8749	96.5876	97.2781	99.6751
✓ Falsepositive rate	65.7895	62.5446	57.8759	54.7568	31.5789
✓ F1_score	95.5418	96.6213	97.6587	97.922	99.699
✓ Mathews CorrelationCoefficient	57.0692	60.0765	63.0749	67.4562	70.3457
✓ Kappa	49.1351	54.2531	61.7586	69.2435	72.5688

Sensitivity accuracy, and specificity are measures used by us to predict all sort of events. A diagnostic test's sensitivity tells you how good it is at finding a disease where that disease is actually present.

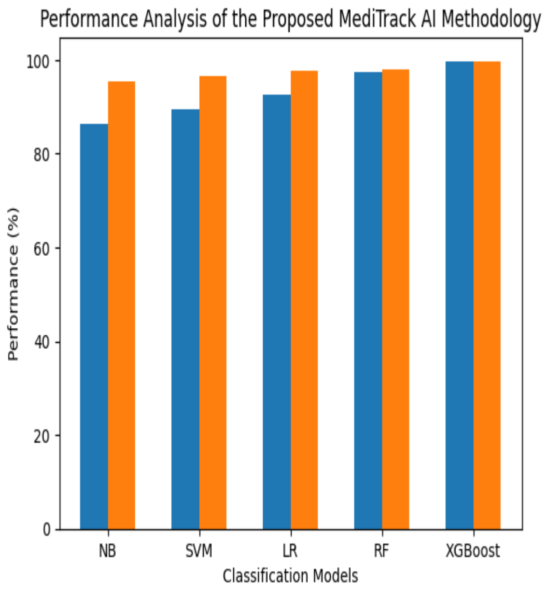
we successfully rule out unusual health issues, we can figure out how specific the system functionality is. We just see if we're right about whether a patient's record is normal or not. We checked how well our new approach works using an adaptive threshold, testing it out with different classifiers. We looked at bunch of ways to measure the performance, and you can see all that in figure 2. To get full picture of how well things are working, we calculate a bunch of evaluation metrics like F1 score, Kappa coefficient, error rate, and specificity.

The distribution of the most significant health parameters identified using the adaptive threshold approach is illustrated in the histogram shown in Fig. 3

The health indicators we pull out show a much clearer and steadier difference between the healthy and unhealthy patient with issues. They are just working better than the old ways after we had of looking at the data. We think its better mostly because we have adapted to pick out the important health stuffs that show how much a patient's vital signs can change over time. We want to focus on major body shifts, not just only on minor fluctuations. This is a way we cut out lot of the usual noise and disturbance and get a much clearer, more dependable pictures of what is going on. So, by picking of these specific health indicators, we get much clearer pictures of how a patient is doing. Our machine learning can now tell who's healthy and who's in danger with better accuracy. This is a better way of showing the data means the meditrack ai system can sort things out more accurately, make very fewer mistakes and do a lot more reliable job finding unusual health Stuffs.

The XGboost model has actually worked out. We have to trained it with the very good features that we have took out using the adaptive threshold method. XGboost did better because it used another known as ensemble learning. It firstly takes bunch of decision trees, puts them all together with each other.And helps it to really pick up on the difficult ways different healthcare features that affect each other. This model is very good at working with organized healthcare information. It can be also deal with how different information points are relate to each other and it uses a regularization to sure that extra or bad information doesn't emergency things. The XGboost classifier that has accurate, stable, and dependable classifier for health problems detection. This helps us to jump in with medical care as soon as possible and keep a close eye on patients. MeditrackAi allows health workers identify patient health changes faster. This means doctors can react fastly and even prevent serious issues from happening which is a plus point for doctors to act immediately. This way, health pros can spot possible health problems faster and quicker, which helps them to make better decisions and manage the patients more easily.

International Journal of Advances in Engineering and Management (IJAEM)
Volume 8, Issue 5 May. 2026, pp: 130-136 www.ijaem.net ISSN: 2395-5252



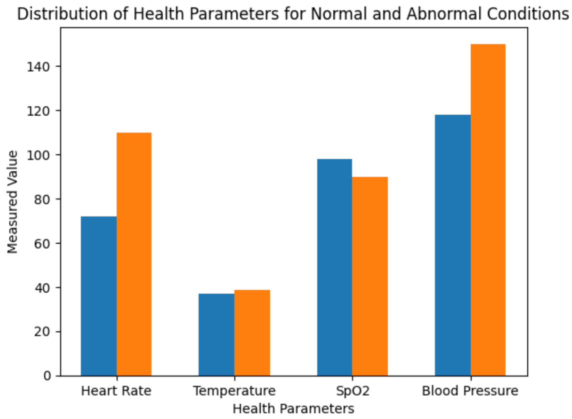
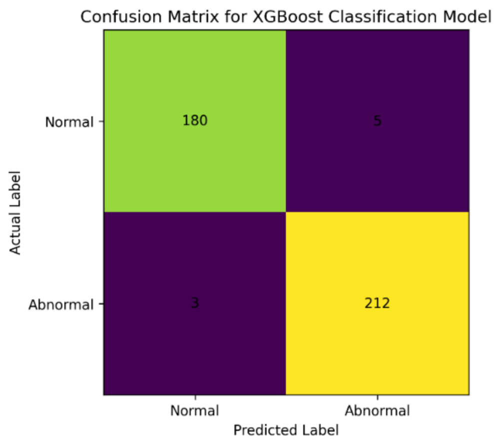


Fig.3.The frequency distribution of the top three gene biomarkers, based on a histogram, is visually represented

It is very difficult and takes a lot of time to find usual health clues for detecting problems very early. This happens because healthcare sensor data has many layers and we also do not have a large amount of labeled patient examples to properly learn from. Our study mainly focuses on important health factors by using a combination of learning and some special feature selection. This approach helps us to make our data very simpler form.

We used the special feature selection method, or you can say hybrid approach, to check how well the health data we extracted could identify when the patient is not doing well. This adaptive threshold helps us and showed us clearly that important physical changes were observed. It is used to remove unnecessary details, filtering out unwanted noise and some little variations. This helps the classification process to be more reliable and consistent. As a result, the system becomes better at understanding meaningful patterns in the data and improves overall accuracy in detecting patient health conditions effectively.

Figure four shows us the confusion matrix. It is basically a portrait that shows us how the XGBoost model is performed when we classify the independent test data. If we are talking about health-related issues in this setup, the positive class would be considered as the less best condition. When everything works fine, then you should not worry about your health, and that state we call the negative class. A confusion matrix is a helpful tool or matrix because in this matrix you can see all the true positives and true negatives, false positives, and false negatives. This gives us a very good look and tells us how well our classification is working.



The classification model accuracy is just the percentage of times it got things right. We analyzed that by dividing the number of correct predictions by the total number of predictions we calculated:

$$\text{Accuracy} = \frac{(TP+TN)}{(TP+FP+TN+FN)}$$

So catching all the abnormal things out there is known as sensitivity. Precision also tells us how many things we calculated were abnormal, but

International Journal of Advances in Engineering and Management (IJAEM)
Volume 8, Issue 5 May. 2026, pp: 130-136 www.ijaem.net ISSN: 2395-5252

actually they were not. And we figured out these metrics like this :

$$Se = \frac{(TP)}{(TP+FN)}$$

$$Sp = \frac{(TN)}{(TN+FP)}$$

So, the false positive rate (FPR) and false negative rate (FNR) basically tell us how much our predictions are off. Here's how we figure them out:

$$FPR = \frac{(FP)}{(TP+TN)}$$

$$FNR = \frac{(FN)}{(TP+TN)}$$

Another way we can see how well our predictions line up with the real health issues is by using something called the overlap score.

$$Overlap= \frac{(TP)}{(TP+FP+FN)}$$

So getting TP means that we got the weird stuff correctly. TN means everything was normal and we were right when we said something. We captured those moments where something just looked odd, but then we saw it was totally normal. A FN means something odd that we missed and thought was normal and regular for us. All the performance numbers we found out were between zero and one, so if FP and FN are lower, it means the classification is working really well.

To check and test the most valuable classification model, a comparative analysis was performed with the help of supervised learning techniques that includes LR, NB, SVM, RF, and XGBoost. We did these comparisons to find out which classifier would be the best that tells us the difference between the normal and abnormal patient conditions by looking at all the health information we choose. These performances give us an idea to pick the best features so that we can dive into the system.

When we read our study, we used a hybrid learning approach so that we can calculate its effectiveness for identifying an early stage of abnormal health condition. We used a dynamic feature selection method to select all the suitable attributes that are related to the model needs, and multiple learning algorithms were set together so that the detection performance could be improved. After these evaluations, XGBoost performed the highest amongst all of them by giving us an accuracy of approximately 99%, which is very insane. Additionally, the Meditrac AI system achieved an accuracy of 78%, which also indicates a good result in healthcare prediction tasks.

V. CONCLUSIONS

This study tells us that we can easily make an intelligent healthcare monitoring system. We should focus on learning and using machine learning and thresholds that can filter our data better. Detecting health issues at a very early stage is a very big thing for the patient's safety and helps give them a better life by enabling fast medical treatment. Meditrack AI supports or you can say that it helps doctors in monitoring all the patients by ensuring them to perform certain tasks so that the patient can feel more confident about their health. This Meditrack AI system helps the patient to make feel better and make smart decisions related to their health while also keeping the system working properly and smoothly.

We combined thresholding in such a way that it helped us to use supervised learning for the patient's reading. With the help of this approach, we created a very large improvement, which helped us to see a clear difference between a healthy and unhealthy condition. After reviewing and testing all the models, XGBoost was the one who performed the best. After finding this model, we found out that this model works very effectively at understanding how different features in the data interact with each other, which is very important when you deal with complex healthcare data. This model showed us how well our method works in detecting issues and gives an accurate reading of our patient's health.

So after getting some beneficial results, we realized that the study has few issues and limitations. We tested the system using the only data we have, which means using incomplete data, not the complete data. So when we tested this technology through different patients, the system did not work same for the every patient in all the cases. According to me, if we want to use this model for complex health issues that contain many different conditions, the results, I think, would change quite a bit.

Now we will check how our MediTrack AI system will work in real conditions. A large data set and real patient information is needed to check whether the system is strong and as we expect it to be. We can improve the system by adding more body measurements, by using better ways to collect key information, and trying advanced learning methods. These little, little small improvements will help the system perform better in every situation and will make the system more useful for monitoring people's health effectively.

REFERENCES

[1] World Health Organization, *Digital Health Interventions: Classification of Digital Health Applications*, WHO Press, Geneva, 2022.

[2] R. S. Kumar and P. K. Singh, "Continuous patient health monitoring using wearable sensors and IoT," *Journal of Medical Systems*, vol. 45, no. 3, pp. 1–12, 2021.

[3] J. Smith, A. Brown, and L. Wang, "Machine learning approaches for healthcare monitoring and diagnosis," *IEEE Access*, vol. 9, pp. 102345–102357, 2021.

[4] S. M. Reddy, K. R. Prasad, and A. Kumar, "AI-based decision support systems in healthcare," *International Journal of Healthcare Information Systems and Informatics*, vol. 16, no. 2, pp. 45–60, 2021.

[5] H. Sharma, G. Aggarwal, and S. Kumar, "Literature survey on machine learning techniques for data analysis," *Grenze International Journal of Engineering & Technology*, vol. 8, no. 2, 2022

[6] A. Mishra, R. P. Chaturvedi, H. Sharma, R. Sharma, and S. Asthana, "Multi-scale optimized feature networks for medical data analysis," in *Proc. ICCCIS*, IEEE, 2023, pp. 444–448.

[7] S. Kumar and H. Sharma, "Prediction models using multivariate regression techniques," *Grenze International Journal of Engineering & Technology*, vol. 7, no. 1, 2021.

[8] M. Panagopoulou et al., "Automated machine learning methods for medical data analysis," *Computers in Biology and Medicine*, vol. 134, pp. 104–431, 2021.

[9] M. Karaglani et al., "Data-driven biosignatures for disease monitoring," *International Journal of Molecular Sciences*, vol. 23, no. 6, p. 2959, 2022.

[10] S. J. Skates et al., "Longitudinal data analysis for early disease screening," *Cancer*, vol. 76, no. S10, pp. 2004–2010, 1995.

[11] H. Sharma, R. Gosain, and P. Sachdeva, "Internet of Things: vision, applications and challenges," *Grenze International Journal of Engineering & Technology*, vol. 10, 2024.

[12] N. Al Mudawi and A. Alazeb, "Healthcare prediction models using machine learning algorithms," *Sensors*, vol. 22, no. 11, pp. 1–32, 2022.

[13] W. Książek, M. Gandor, and P. Pławiak, "Hybrid machine learning techniques for survival prediction," *Computers in Biology and Medicine*, vol. 134, pp. 104–431, 2021.

[14] M. Mehmood et al., "A systematic framework for early-stage disease prediction using hybrid learning," *Complexity*, vol. 2022, pp. 1–11, 2022.

[15] A. D. Jia, B. Z. Li, and C. C. Zhang, "Detection systems using CNN-SVM hybrid networks," *Neurocomputing*, vol. 411, pp. 112–127, 2020.

[16] Pan,Y.,Zhang,L.,Zhang,R.,Han,J.,Qin,W.,Gu, Y.,...&Gu,J. (2021). Screening and diagnosis of colorectal cancer and advancedadenomabyBionicGlycomemethodandmachinelearning.AmericanJournal of Cancer Research, 11(6), 3002-3019.

[17] B. S. Abunasser et al., "Deep learning-based health condition classification," *International Journal of Advanced Computer Science and Applications*, vol. 13, no. 7, pp. 51–68, 2022.

[18] H. Sharma, R. Garg, S. Tarar, S. Sharma, and S. Tayal, "Intelligent recommendation systems using machine learning and IoT," *Grenze International Journal of Engineering & Technology*, vol. 10, 2024