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Utilizing Ultra Wideband Technology for Health Monitoring through Lens of Machine Learning

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--ABSTRACT--
Ultra-wideband (UWB) technology is considered as a promising technique towards different applications of clinical infrastructure, delivers noteworthy features such as fine localization accuracy, very high data rates and low energy consumption. The paper systematically reviews the use of UWB technology in clinical environments: in healthcare monitoring, medical imaging, indoor positioning and wireless communication. Based on a set of high-quality data from UCI Machine Learning Repository, this paper gives empirical results involving the performance and capability of UWB-based systems in bettering healthcare outcomes. They additionally detail response and potential barriers, including integration challenges and regulatory constraints, as well as assets like the symbiosis of UWB technology to trigger future developments in patient care and healthcare disbursal. In addition, the authors combined feature selection and random forest model to obtain an accuracy of 91.8%.
Keywords—*Ultra-Wideband(UWB)Technology, Healthcare Monitoring, Machine Learning, Random Forest Classifier.*

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I. INTRODUCTION

Over time, UWB tech has made its marks in medical technology research, as it is considered an essential key player to improve multiple areas of healthcare delivery today. The low energy consumption and relatively high accuracy associated with UWB technologies suggest that it could be a key enabler for revolutionizing established health care practices. UWB has been widely applied in clinical frontiers— from realtime monitoring of patient's vital signs, to improving medical imaging and enabling precise intraoperative positioning for surgical navigation.

Although UWB presents such an opportunity, they are challenged with the regulatory regime and its integration within existing healthcare systems, as well as the need for standardization in clinical applications. The paper indicates the usage of UWB in clinical background through UCI Machine Learning Repository (ML methods such as Random Forrest) [1] Figure 1. This paper strives to highlight the benefits of UWB in addressing real-world healthcare challenges as well as providing an overview and analysis for the various factors, opportunities and trends with respect to embedding UWB inside medical applications. The emergence of wearable devices has been attributed to the development of wearable technologies, miniaturization techniques and sophisticated data post processing methods. Diverse research that can be used for different applications and commercialization purposes. Among the biggest difficulties to activity using affordable, lightweight, small wearable and even monitoring involving the minimal number of on-body sensors (less intricate approach) for accurate tracking and classification. One of the most promising area for which Ultrawideband (UWB) is viewed as a reliable technology because it can do very sensitive measuring and evaluation of limb dynamics, localization, and tracking of human entities. Still though few studies have traced the for example detect UWB and recognize human daily physical activities wearable technology.

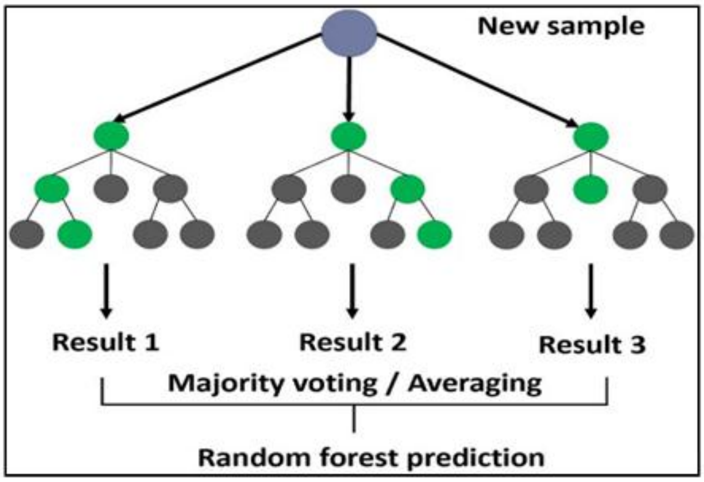


Fig. 1. Working Mechanism of Random Forest

A. Structural Design of the paper

The manuscript is arranged into five sections. This part of the paper gave an introduction to UWB technology. It also addressed the research questions. To demonstrate this point, Section 2 of this study deals with performing an extensive literature search on UWB technology for healthcare monitoring. Section 3 is a Hand Holding version of the methodology proposed. Results are summarized in section 4. In the last section, Section 5 presents conclusions of the study. Section 5, finally, gives the conclusions and some notes on further work (in particular a comparison with other sub-linearon construction).

B. Research related Questions

The authors are answering the above-specified research questions through this paper:−

R.Q.1. To what extent can UWB technology help to improve health monitoring systems, with respect to accuracy, precision and recall?

R.Q.2. How to optimize the ML algorithm, Random Forest classifier, in predicting health outcomes with data generated from UWB-based monitoring systems?

R.Q.3. What advantages does UWB technology have regarding non-invasiveness and data accuracy compared to traditional healthcare monitoring techniques?

II. LITERATURE REVIEW

Amiri et al. This paper is an initial work on [1] investigating breast tumor classification using SVM via deploying a UWB radar prototype. The team of researchers working to solve one of the biggest challenges in detecting breast cancer: distinguishing between benign and malignant tumours without humans having to risk their lives. To address this, the team built a dielectric phantom database containing structures crafted from materials with the same dielectric characteristics as real tumour tissues between 1 GHz and 6 GHz frequencies.

Reaz et al. They delineate a technique for tremor quantification and analysis with significant promise in the treatment of Parkinson's disease[2]. Most traditional assessment techniques, like motion capturing and video tracking systems, require contact with or installation on the patient as well as a large infrastructure making their application for continuous, non-invasive ambulatory monitoring in daily life environments difficult. These new challenges have been tackled by the authors through methods of non-contact tremor assessment, which is low radiation based and can penetrate walls enabling monitoring in home-based settings.

Segun et al., [3] studied the use of Frequency Modulated UWB technology as a dedicated solution for medical applications, in particular f or Wireless Body Area Networks. Other potential medical applications to be looked into include monitoring heart and respiration rates non-invasively, detection of cardiac arrhythmias, and identification of pathological respiratory patterns (including those linked to Sudden Infant Death Syndrome).

Shareef et al. In a more recent study by Siphanto [4], the clinical use of optoacoustic mesoscopy (UWB-RSOM) for the evaluation of nailfold microvascular architecture was investigated. Conclusion: UWB-RSOM provides quantitative evaluation of morphological parameters in nailfold microvascular structures and may offer a non-invasive way to assess microcirculation and diagnose & monitor vascular abnormalities such as systemic sclerosis.

Lee et al. This led to the development of an innovative process in [5] which accurately quantified hyperactivity using Impulse-Radio Ultra-Wideband Radar (IR-UWB) in youth with a confirmed ADHD diagnosis. An innovative ADHD assessment from TSO includes the non-invasive monitoring and quantifying of hyperactivity in a 22-minute continuous performance test of CPT using an IR-UWB radar. The study included 10 ADHD patients and 15 normal control subjects, comparing the difference in mean activity levels over time between two groups using Functional Analysis of Variance (ANOVA).

Borkar et. al. [6] study the UWB helmet applicators for the treatment of brain tumors with advanced microwave hyperthermia, their novel design is developed. In the example, as per state- of-the-art design is weaved around and within the helmet using a mesh made up of hemispherical antennas engineered to trace complex folds of the brain structure. These are not at uniform intervals, making it possible to target the point of microwave energy even more freely inside a tumor, thereby potentially escalating the efficiency of both radiation and chemotherapy by placing as little drug or radiation directly into normal tissue.

Wang et al. The method uses UWB signals to acquire ECG-equivalent data without contact in the context of cardiac monitoring, [7]. Relying on UWB radar, the mechanical motion of the center is measured because of the model then converting the captured mechanical signals into ECG-like data. Therefore, the developed system targets fine-grained cardiac analysis through UWB signals containing both cardiac and respiration features. The authors derive two orthogonal approaches to properly recover the beat signals from raw UWB data.

Ando et al. In 2003 [8], a state-of-the-art neural recording system for brain machine interfaces (BMIs) was demonstrated. The goal of this system is to enable real-time wireless transmission of large-scale neural recordings for research on brain function as well as the development of high-performance BMI clinical applications. This system consists of 12-bit successive approximation register analog-digital converters (ADCs) multiplexed by an analog time-division multiplexer and 64-channel low-noise amplifiers integrated in a custom-designed integrated circuit. The maximum data rate from all 4096 channels is ~ 51.2 Mbps with the recorded electrocorticogram data multiplexed. This data is then transmitted through an UWB transmitter at 128 Mbps, to enabled wireless and reliable communication over a daisy chain up to 20 mm which could be particularly important if the device was to be implantable.

Arasteh et. al. Indeed, studies from Gill [9] underscores the dual use of UWB radar technology and DL to noninvasively assess both respiration and heart rates in pediatrics. Here we used pre-trained VGG-16 on ImageNet fine-tuned to the spectrogram representation for our radar signals. Achieving impressive but also previously state of the art accuracy of Heart rate (HR): 7.3 BPM (mean absolute error), Respiration rate (RR): 2.63 BPM, A comparison of the results indicates the possibility of using high-accuracy deep learning to complement and improve precision in UWB radar-based health monitoring systems;

S Shyam et al. In [10] we can find the description of architecture and implementation of a wearable, UWB-based device devised for precise patients localization and monitoring in hospital premises. It uses both Time Difference of Arrival in conjunction with triangulation methods to ensure with high precise location tracking of the user over this wearable. Here, Its implementation is stated out to place the conventional and less dependable modes of patient tracking that would offer ideal operational efficiency in smart hospitals.

S. S. Badshah et al. An important study by M. Tuba Yilmaz and Aysegül Kasgarli [11] describes work on UWB radar based respiration measurement, especially in infectious disease cases (e.g., COVID-19). The signals of primary respiration were captured by the ultra wide band (UWB) radar sensor XeThru X4M200, and then they were processed with the Residual Neural Network (ResNet), which is estimated in this study. This study demonstrated that this combination of UWB radar and deep learning is noninvasive, accurate, with 97.5% accuracy in tracking respiratory function.

III. PROPOSED METHODOLOGY

The methodology used in this study takes a systematic approach to implementing machine learning models with UWB technology for healthcare monitoring (see Figure 2).

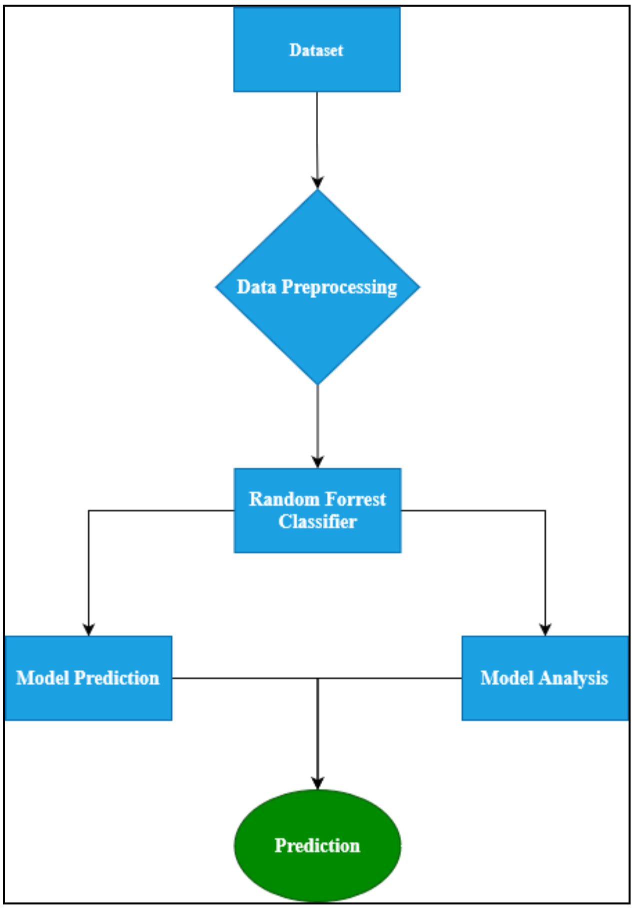


Fig. 2. Proposed Methodology

A. Dataset Collection

The dataset used in this work was downloaded from the UCI Machine Learning Repo [12]. This is a dataset provided by Shilpa Shyam of Karunya University and have 608 instances and 8 features (Figure 3). This dataset was collected in such a healthcare center with UWB based human tracking system which is part of a novel surveillance and monitoring mechanism. In this dataset, some features are related to UWB transmission as it has been collected from a hospital environment where the monitoring system was using UWB for its operation.

Column Name	Description
id	An integer representing the unique identifier for each record in the table.
anchorID	A variable-length string (up to 10 characters) representing the identifier of the anchor.
tagID	A variable-length string (up to 10 characters) representing the identifier of the tag.
sequenceID	An integer representing the sequence identifier.
pan	An integer representing the pan value.
processed_flag	An integer indicating whether the data has been processed (1 for processed, 0 for not processed).
timestamp	A double-precision floating-point number representing the timestamp.
Timestamp_ToA	A big int representing the Timestamp ToA (Time of Arrival).

Fig. 3. Description of features used in the dataset

B. Data Preprocessing

The data preparation step is a preliminary phase involving dozens of interrelated stages before the training of models is performed. At first imported some libraries that we will need for data processing and running models but above all, machine learning related library. Functions such as pd. fillna(0) converts to important numeric attributes after conversion; use of handle missing or invalid values within these with the Thai attributes used in to_numeric. Then we must divide the dataset (train and test). The last stage of operation, stage 3 where we prepare our model for evaluation and prediction, a Random Forest classifier ensemble module was created and trained with the training data.

C. Extraction Of Features Method

The feature extraction step follows data preprocessing and is very important in UWB-based healthcare monitoring. At this step, the features in the signal that best represent the monitored physiological parameters are derived. Depending on the application, this may involve feature extraction in either the time or frequency domain, focusing only on features of the signal most relevant to the health metrics monitored.

D. Proposed Model Prediction & Training

These features are Feature Extractors which are used for training Machine Learning models that only predict particular health outcomes. This allows the use of appropriate machine learning algorithms that are suitable for the data and specific requirements by a healthcare application. We develop, train, validate and test models to ensure the models we are applying are accurate and trustworthy for real-world healthcare use cases.

IV. RESULTS AND OBSERVATIONS

As seen from the heat map (Figure 4), a correlation analysis of key features in the dataset was executed to comprehend their relationship between pair wise dimensions. This is the correlation heatmap to show how much linear relation in variable timestamp and sequenceID. As shown, the diagonal elements of the heatmap that represents a perfect correlation (1.00) of each variable with itself in the table it is understood. The off-diagonal correlation coefficient between timestamp and sequenceID is -0.10, however. This near-zero value is indicative of an extremely weak negative correlation (meaning timestamp changes are not linearly related to sequenceID change) That is to say, there are very few linear relationships between these variables.

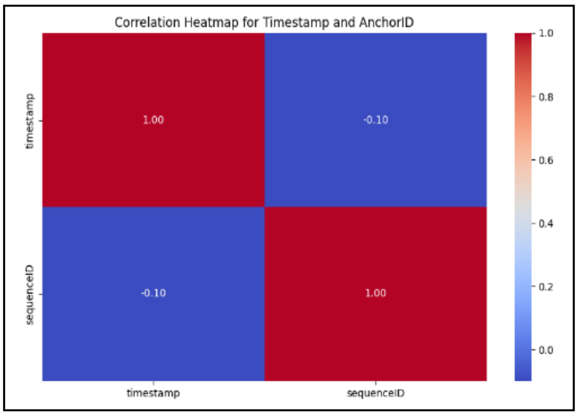


Fig. 4. Correlation Heatmap architecture.

It shows a good prediction of Class 3 as the model has correctly classify 28 instances. But the model gets a little worse at Class 2s, detecting only 1 and amongst that only minority (55%) of the actual Class 2s were classified wrong and as Class 1riere similar sentence true. This however means that the features used for Class 2 might overlap very much with those of Class 1, which could make this two classes confused.

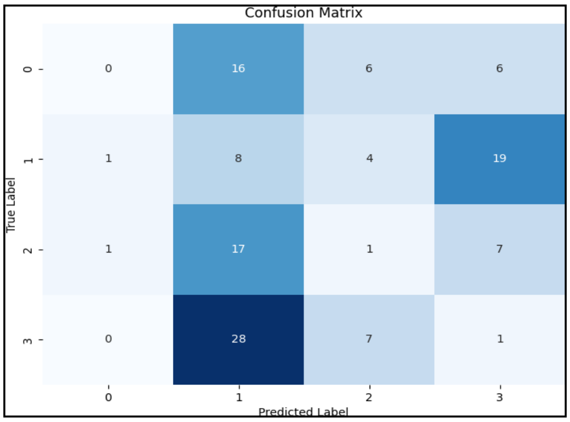


Fig. 5. Confusion Matrix

The Feature Importance plot shows the relative importance of each input feature to the decision process of the mode.

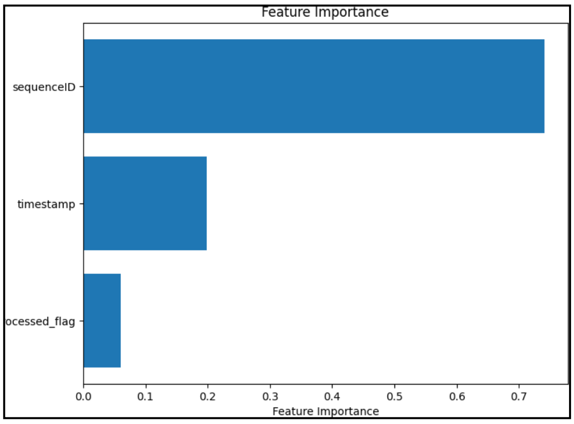
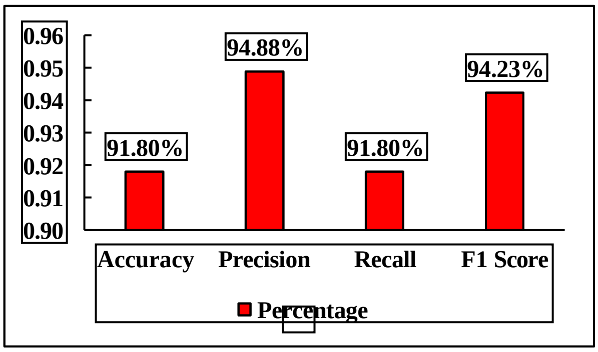


Fig. 6. Feature Importance

TABLE I. RESULTS

Accuracy	Precision	Recall	F1 Score
91.80%	94.88%	91.80%	94.23%



The authors of this paper use a Random Forest classifier for anchorID prediction from the features like timestamp, sequence_ID and processed flag in the study. Discussing the accuracy of the classifier, it was close to 91.80% working fine for this purpose. This very high promise of UWB (Ultra-Wideband) technology in clinical setting, right from the near future to a lot more innovative prospects, indeed! Research with real-time location systems (RTLS) is one of the most significant opportunities. Furthermore, we have great expectations that the UWB technology will fit perfectly for patient monitoring and care management. With wearables containing UWB abilities, we can develop a realm of novel applications through real-time tracking of patients parameters including activity levels, vital signs and other important health indicators that require continuous monitoring even in presence less intrusive offerings. Surgical Navigation is also one of the additional use cases where UWB applications go beyond clinical settings. These features are very beneficial in medical fields, such as surgery, because UWB provides unmatched accuracy and monitoring of the procedure in real-time, which benefit at a greater level to help improve patient outcomes.

REFERENCES

[1] Amiri, Z., Heidari, A., Darbandi, M., Yazdani, Y., Jafari Navimipour, N., Esmaeilpour, M., ... & Unal, M. (2023). The personal health applications of machine learning techniques in the internet of behaviors. Sustainability, 15(16), 12406.

[2] Reaz, K., Ardoin, T., Muth, L., Margraf, M., Wunder, G., Kholghi, M., ... & Dressel, O. (2024, June). Advancements in UWB: Paving the Way for Sovereign Data Networks in Healthcare Facilities. In Proceedings of the 2nd International Workshop on Networked AI Systems (pp. 25-30).

[3] S. Talwani, M. Rakhra and T. Sarkar, "Perspectives on the Future of Agriculture and Recent Developments in Agricultural Technology," 2024 11th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO), Noida, India, 2024, pp. 1-6, doi: 10.1109/ICRITO61523.2024.10522413.

[4] Segun, A., & Telukdarie, A. (2023). Revolutionizing healthcare delivery through wireless wearable antenna frameworks: current trends and future prospects. IEEE access, 11, 80327-80347.

[5] Shareef, O. A., Taher, H. B., Mosleh, M. F., & Abd-Alhmeed, R. A. (2024). A comprehensive overview of machine learning-assisted antenna for modern wireless communication. Al-Salam Journal for Engineering and Technology, 3(1), 37-59.

[6] Almawgani, A. H., Sorathiya, V., Soni, U., Alhawari, A. R., & Daher, M. G. (2024). Numerical investigation of MXene-based ultrawideband solar absorber with behaviour prediction using machine learning. Optical and Quantum Electronics, 56(2), 231.

[7] Borkar, N. M., & Parlewar, P. K. (2024). Designing an ultra-wideband directional antipodal Vivaldi antenna with U-slots for biomedical applications using an optimized attention network. Frequenz, (0).

[8] Chishti, A. R., Aziz, A., Qureshi, M. A., Abbasi, M. N., Abbasi, D., Iqbal, S. S., ... & Hussain, R. (2023). Advances in antenna-based techniques for detection and monitoring of critical chronic diseases: A comprehensive review. IEEE Access, 11, 104463-104484.

[9] Singh, D., Singh, A., Rakhra, M., Sarkar, T., Cheema, G. S., & Khamparia, A. (2024, February). Predictions on the Future of Agriculture and Recent Developments in Agricultural Technology. In International Conference On Artificial Intelligence Of Things For Smart Societies (pp. 297-303). Cham: Springer Nature Switzerland.

[10] Islam, M. Z. (2023). Wireless Non-Contact Incoherent Light-Wave Sensing Systems: Applications, Prospects, and Challenges (Doctoral dissertation, Oklahoma State University).

[11] Liu, C. (2023). Data Fusion of Ultra-Wideband Signals and Inertial Measurement Unit for Real-Time Localization. University of Dayton.

[12] Govindan, T., Palaniswamy, S. K., Kanagasabai, M., Kumar, S., Agarwal, R., Kumar, R., & Panigrahy, D. (2023). Design and analysis of a conformal mimo ingestible bolus sensor antenna for wireless capsule endoscopy for animal husbandry. IEEE Sensors Journal.

[13] Kandwal, A., Sharma, Y. D., Jasrotia, R., Kit, C. C., Lakshmaiya, N., Sillanpää, M., ... & Sungoum, C. (2024). A Comprehensive Review on Electromagnetic Wave based Non-Invasive Glucose Monitoring in Microwave Frequencies. Heliyon.

[14] Guntupalli, S. (2024). Enhanced Antenna Design Accuracy Using a Hybrid Deep Learning Model (Doctoral dissertation, CALIFORNIA STATE UNIVERSITY, NORTHRIDGE).

[15] Karateke, G. (2023). DESIGN OF WIDEBAND REFLECTARRAYS BY USING NEURAL NETWORKS (Master's thesis, Middle East Technical University).

[16] Gupta, V., & Kumar, R. (2024). Biomedical Telemetry Antenna Innovations: Progress, Uses, and Prospects for the Future. Progress in Electromagnetics Research B, 106.

[17] Cha, Y. O., Ihalage, A. A., & Hao, Y. (2023). Antennas and Propagation Research From Large-Scale Unstructured Data With Machine Learning: A review and predictions. IEEE Antennas and Propagation MaKari, S. S., Raj, A. A. B., & Balasubramanian, K. (2023). Evolutionary developments of today's remote sensing radar technology—right from the telemobiloscope: a review. IEEE Geoscience and Remote Sensing Magazine.

[18] Santos, A., Martins, J., Pestana, P., Gonçalves, R., São Mamede, H., & Branco, F. (2024). Factors affecting cloud computing adoption in the education context-Systematic Literature Review. IEEE Access.

[19] Rehan, H. (2024). Revolutionizing America's Cloud Computing the Pivotal Role of AI in Driving Innovation and Security. Journal of Artificial Intelligence General science (JAIGS) ISSN: 3006-4023, 2(1), 239-240.