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Seamless navigation for indoor-outdoor positioning using GNSS-aided UWB/WiFi/IMU system

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BIOGRAPHY

Akpojoto Siemuri received his B.Sc.(tech) degree in electrical and computer engineering from the Federal University of Technology Minna, Nigeria in 2010, an M.Sc.(tech) degree in wireless industrial automation with a minor study in industrial management from the University of Vaasa, Finland in 2019. He is currently pursuing a Ph.D. degree in automation technology at the University of Vaasa. From 2018 to 2019, he was a Research Assistant in the Smart Energy Systems Research Platform (SESP) Project at the University of Vaasa, Finland. He is currently a Project Researcher at the University of Vaasa. His research interest includes machine learning, GNSS technologies, Factor graphs, smart devices, embedded systems, communication systems, and game theory.

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Dr. Heidi Kuusniemi is a professor of computer science and director of Digital Economy at the University of Vaasa in Finland. She is also a part-time research professor in satellite navigation at the Finnish Geospatial Research Institute. She has an M.Sc. (Tech.) degree (with distinction) from 2002 and a D.Sc. (Tech.) degree from 2005 in information technology, respectively, from Tampere University of Technology, Finland. She served as a member of the Council of Natural Sciences and Technology at the Academy of Finland 2019-2021 and was a member of the scientific advisory committee for GNSS (GSAC) at ESA. Her technical expertise and interests include GNSS reliability and resilience, estimation and data fusion, mobile precision positioning, indoor localization, and PNT in new space.

Prof. Mohammed S. Elmusrati received his B.Sc. (with honors) and M.Sc. (with high honors) degrees in electrical and electronic engineering, from the University of Benghazi, Libya, in 1991 and 1995, respectively, and the Licentiate of Science in Technology (with distinction) and the Doctor of Science in Technology (D.Sc.) degrees in automation and control engineering from Aalto University Finland, in 2002 and 2004, respectively. Currently, he is a Full Professor and Head of the Digitalization Unit at the School of Technology and Innovations – University of Vaasa, Finland. His research interest includes wireless communications, artificial intelligence, machine learning, biotechnology, big data analysis, stochastic systems, and game theory. Elmusrati has published more than 130 papers, books, and book chapters. Prof. Elmusrati is an active member of different scientific societies such as a Senior Member at IEEE, a Member of the Society of Industrial and Applied Mathematics (SIAM), and a Member of the Finnish Automation Society.

ABSTRACT

The need for seamless indoor-outdoor navigation is growing in different application fields, especially for factory scenarios, military, or first response emergency services. Multi-sensor fusion technology has become very prominent for seamless navigation systems owing to its complementary capabilities to Global Navigation Satellite System (GNSS) positioning. Machine learning (ML) and artificial intelligence (AI) solutions have also been widely adopted in literature in the last few years combining them with localization techniques for error mitigation and maximizing overall accuracy and system integrity. The research work of this paper is aimed at the following: firstly, to design an indoor-outdoor (IO) detection strategy that helps to correctly identify the transition between outdoor and indoor with reduced latency; secondly, to construct two separate integration schemes. GNSS integrated with indoor positioning technology (GNSS/UWB/IMU and GNSS/WiFi/IMU) can account for the GNSS signal distortion in indoor and urban environments. Based on this context, a loosely coupled architecture is implemented. The GNSS receiver helps the IMU to update with absolute positions from GNSS in the outdoor scenario. This positioning strategy takes advantage of both GNSS and UWB/IMU/WiFi combinations to realize a seamless indoor-outdoor positioning for personnel and indoor robots moving between the outdoor and indoor environments. The correct detection of the IO transition is essential in seamless IO positioning. This enables making the right decision on the navigation mode. Our implementation of indoor-outdoor (IO) detection strategies makes use of ML to find the IO signal transition pattern. The proposed system would be tested in a scenario over 1.1 km including outdoor, and indoor phases.

Keywords - Seamless positioning; Indoor-outdoor (IO) detection; Machine Learning; RINEX data.

I. INTRODUCTION

Global Navigation Satellite System (GNSS) is still a popular technique for outdoor positioning and navigation. However, it is limited and has well-known vulnerabilities when exposed to constrained environments such as urban canyons and indoor environments due to phenomena such as multi-path, Non-Line-of-Sight (NLOS) reception, and signal blockage. Some of these errors and vulnerabilities can be taken care of using techniques that help monitor the GNSS measurement quality, such as Fault Detection and Exclusion (FDE). In addition, certain GNSS system errors can even be directly removed by applying more accurate corrections, such as Precise Point Positioning (PPP). This is applicable to errors due to urban environments, however, there still remains the issue of indoor environments where it is impossible to use GNSS standalone.

There are a number of techniques that are being used to address indoor positioning, from the well-known Inertial Measurement Unit (IMU) to other technologies such as Wi-Fi positioning [1], Ultra-wideband (UWB) positioning [2], [3], Bluetooth low energy (BLE) or Bluetooth positioning [4], camera-based positioning [5], etc. These technologies are usually combined together so as to make the system more robust for different indoor contexts or scenarios.

There has been an increase in the amount of research work done based on the various developments of indoor and outdoor navigation technologies as mentioned above. This has increased the focus on seamless indoor-outdoor navigation. The main issues in the field of seamless indoor-outdoor navigation are not limited to only the choice of positioning techniques and algorithms, but also the detection of the transition between indoor-outdoor. In this work, we will develop a high-precision seamless navigation system for light indoor to outdoor positioning using ML-based indoor-outdoor (IO) detection strategies. Many works address the issue of detecting indoor/outdoor environments. In [6] seamless pedestrian positioning and navigation were developed using landmarks detection ML models. An ML-based IO signal transition pattern detection was implemented to determine the signal pattern transition between indoors/outdoors. [7].

The difference between open outdoors and semi-outdoors, light indoors, and deep outdoors is the number of satellites in view. In open outdoor environments, we have at any moment at least four satellites available, which means the localization of the user can be done using GNSS, while in semi-outdoors, light indoors, and deep indoors environments, the number of visible satellites begins to reduce as you progress to deep indoors. Then there is not enough satellite for GNSS localization. The difference between light indoors and deep indoors is the visibility of navigation satellites. In light indoor environments, users may receive navigation signals from several satellites and therefore can be localized using peer-to-peer cooperative positioning, however, in deep indoor environments, no navigation satellites are available. In that case, cooperative positioning fails.

Within the campus of the University of Vaasa, lies Technobothnia the reputable industrial venue having a modern laboratory serving a minimum of five universities and other corporations in the Vaasa region. It has several laboratories for all kinds of technical sciences for example, industrial robots, smart operations, mobile robots, chemistry labs, heavy-duty 3D printing machines, telecommunications equipment, etc. Therefore, visitor traffic is high, and this brings about the need for a seamless outdoor/indoor positioning system that will be beneficial to both human operators and robot assets inside the laboratory. This building has been used as our test indoor environment.

Indoor-outdoor navigation systems can be used to fulfill the following tasks depending on the requirements:

1. location determination;

2. building a route to the desired point, including between buildings within the territory;
3. real-time turn-by-turn navigation;
4. collecting geodata for analytics;
5. sending out push notifications with tips and other information.

In our work, we proposed to use the C/NO value of the GNSS signal and the number of available GNSS satellites to detect the transition between indoor/outdoor environments. By analyzing the C/NO value of the GNSS signal and making use of the available GNSS satellites in view, we can determine the user's environment. We have investigated some machine learning algorithms for classification, including Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), Logistic Regression (LR), Naive Bayesian (NB), and Neural Network (NN).

The results of the experiment showed that the proposed algorithm was capable of detecting open outdoors, and light-indoor environments with up to 100% accuracy. The hardware and signals required for this are easily accessible and used in our daily lives.

The rest of the article is organized as follows: Section II describes the materials, methods, and strategies used in this research and the essential elements (software and hardware) to build the IO detection model. Section III defines the steps taken during the implementation of the IO detection model. Section IV discusses the output results and provides technical interpretations, evaluations, and comments on the applied performance metrics. In the conclusion section V, the overall achievements are highlighted, and potential future work is presented.

II. MATERIALS, METHODOLOGIES, AND MODELS

In our work, the proposed algorithm is categorized into two main stages: Data Input, ML-based IO detection model training and testing. An overview of the indoor/outdoor detection process is illustrated in Figure 1.

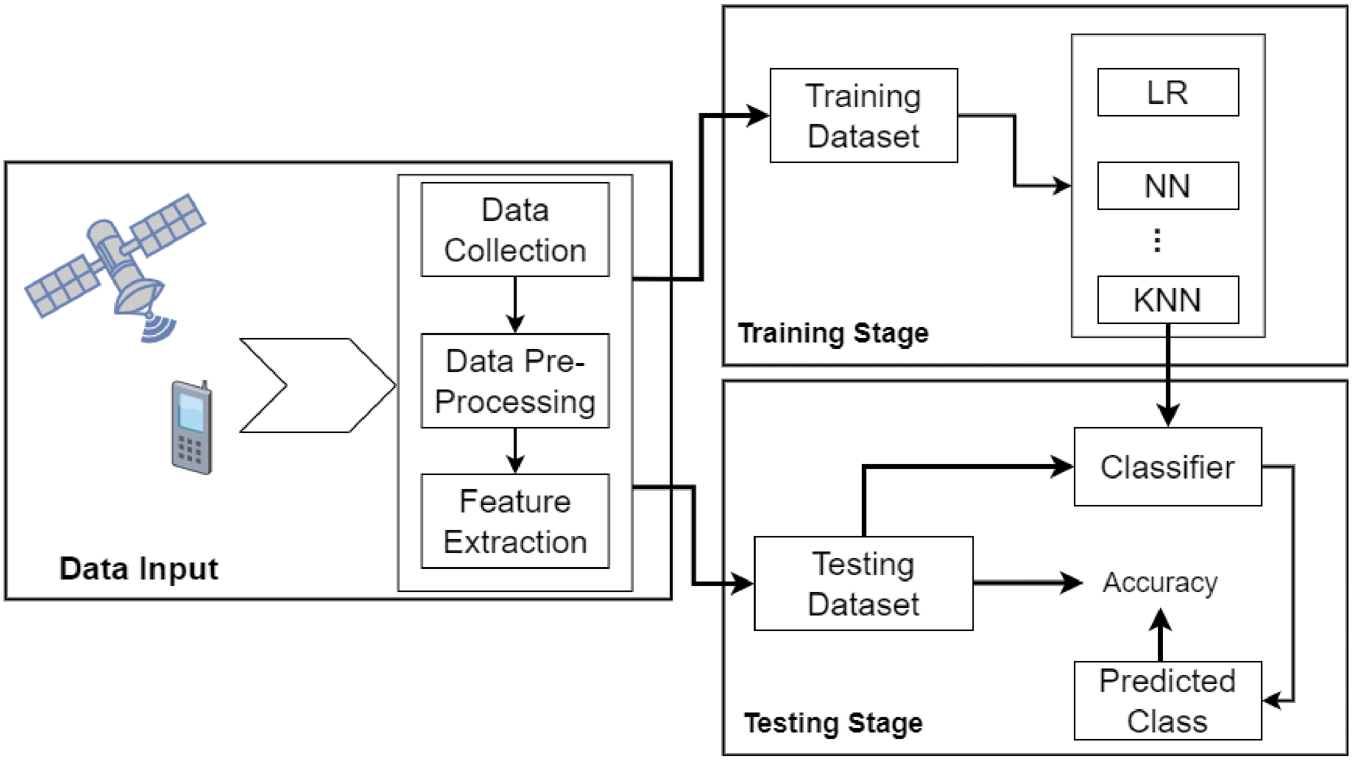


Figure 1: Framework for indoor/outdoor detection. The three processes in this framework include Data Input, Training, and Testing. In the Data Input process, GNSS observation data is recorded, and features are extracted. The data are classified in the Training phase. The classifier is applied to detect the user's current environment in the Testing phase.

1. Data Input

Three sub-processes are included in the data input stage: Data Collection, Pre-Processing, and Feature Extraction.

a). Data Collection

Regarding the format of the collected data, receivers use their own propriety (binary) formats, but programs can be used to convert the data into a standard format called Receiver Independent Exchange Format (RINEX) which can be regarded as the most common GNSS Data file format. The RINEX data can be divided into two, namely RINEX Data header and RINEX Data block.

We used an Android smartphone with an application capable of capturing raw RINEX observables. The smartphone used was the Samsung Galaxy Note20 Ultra. The software used was the GEO++ RINEX Logger.

In this process, the Geo++ RINEX Logger uses the most recent Android API services to log the device's raw GNSS measurement data into a RINEX file. The GNSS data are collected for the test area. The outdoor-indoor positioning is performed in Technobothnia. The UWB (Decawave), Wi-Fi, and IMU (Xsense) data are collected in the Technobothnia building using their respective sensors mounted on a robot (Omron robot).

b). Data pre-processing

The data is then analyzed and pre-processed for use in the IO positioning model. A Python script was developed and used to implement the processing strategy. The recorded GNSS RINEX observation data is processed and parsed using a Python script. The processed data is analyzed before use in the ML-based IO detection model. The features to be extracted are included in the parsed RINEX data.

c). Feature Extraction

In each processed RINEX file, we can extract several features to describe the character of the environment. These features include pseudorange in meters, carrier phase in meters, Doppler, C/N0 in DbHz, and the number of available satellites per epoch.

Pseudorange: Pseudorange is the measured range between the phase centers of the GNSS satellite and receiver antennas, plus the offset between the transmitter and receiver clocks.

Carrier phase: The carrier phase measurement is the measurement of the beat frequency between the satellite signal's received carrier and a reference frequency generated by the receiver. It is the difference between the receiver oscillator phase and the signal received plus the number of cycles at the initial start of tracking.

Doppler shift: In order to be able to receive the signal, the receiver does an estimation of the Doppler shift of each received signal. The time derivative of a signal's carrier phase gives the Doppler shift of the signal. Therefore, the Doppler shift is mainly determined using the relative velocity of the satellite's and receiver's antennas, plus a common offset proportional to the receiver's clock frequency error.

Number of available satellites: The number of available satellites depends on the environment. In the open outdoor environment, no matter whether on water or on a highway, we can localize ourselves using GNSS [8]. In the indoor environment, the number of available satellites is greatly reduced as you go deep indoors. This has a degrading effect on the localization of the user using GNSS, and it becomes impossible in the deep indoors.

2. ML base indoor-outdoor (IO) detection strategy

The correct detection of the IO transition is essential in seamless IO positioning. This enables making the right decision on the navigation mode. The implementation of indoor-outdoor (IO) detection strategies makes use of ML to recognize certain landmarks as well as to find the IO signal transition pattern.

a). Training

In the training stage, we investigate some machine learning algorithms to classify the training data. These ML algorithms include Random Forest (RF), Support Vector Machines (SVM) like support vector classifier (SVC) and Linear SVC, Logistic Regression (LR), Naive Bayesian (NB), and Neural Networks. The classifiers are applied for Indoors/outdoor (IO) recognition. The training data are the raw RINEX data from the GNSS sensors on the smartphone. The best classifier will be selected for indoor/outdoor detection.

b). Testing

The testing phase is used to categorize new samples using the classifiers created in the training phase by the machine learning algorithms. The results show the different performances of the implemented ML algorithms. The performance measures for multi-class classification proposed by researchers have been applied. A confusion matrix was proposed to evaluate the performance of a classification system for the 2-class samples.

To evaluate the IO detection performance, we have made use of the following performance measures:

The testing indoor environment for this experiment is shown in Figure 2. The IO transition is made from outside the building to the section highlighted with green lines for the robot's trajectory inside the building.

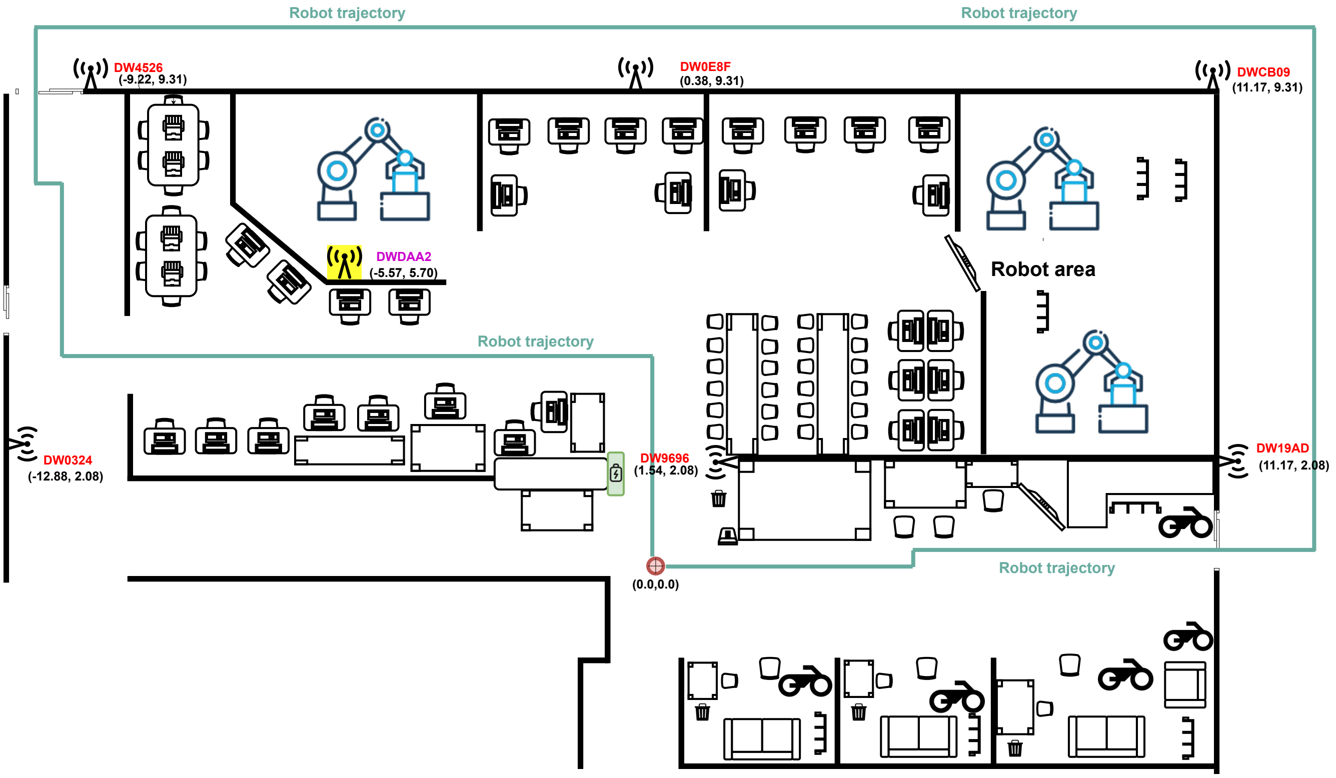


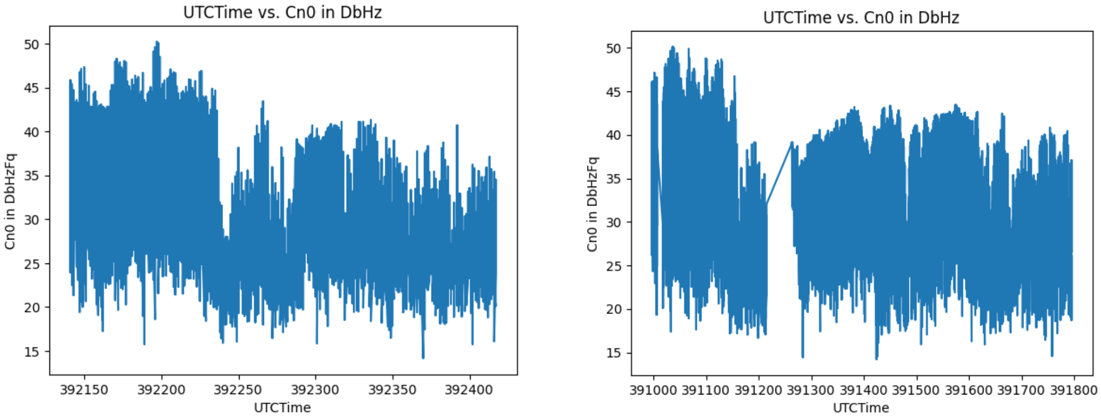
Figure 2: Floor plan of Technobothnia laboratory with the planned robot trajectory.

III. EXPERIMENTS

To test the IO detection algorithm, we make use of separate data (the test data) not shown to the ML-based IO detection models during training. The trained ML classifiers are used to predict the detected environment.

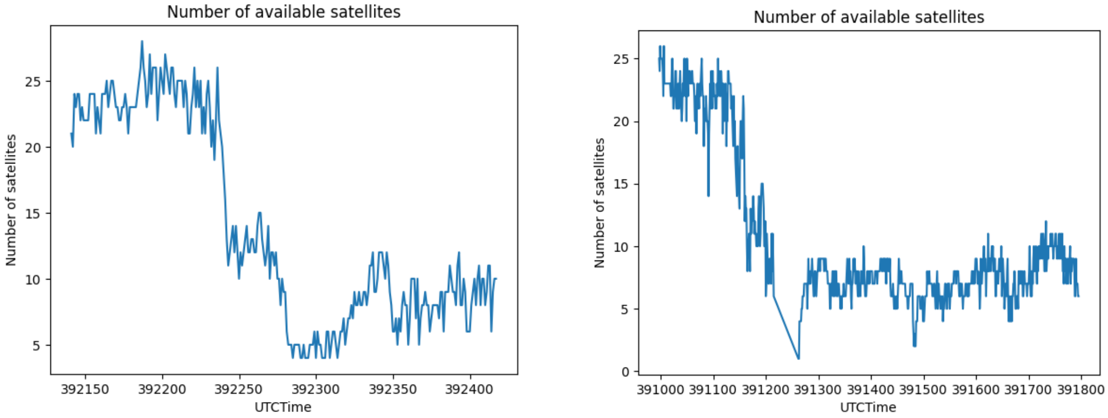
From Figure 3 (c) and (d), we can see the sharp drop in the number of satellites after some UTC time epoch. This drop was noticed during the transition from outdoor to indoor (light-indoor). The number of satellites kept fluctuating during the time when moving around the indoor environment. This is also seen in Figure 3 (a) and (b) for the C/NO values.

The ML IO detection model is trained to detect the transition pattern, and this can be used in the selection of the appropriate positioning technology to apply. With this, the system can switch from the GNSS/IMU positioning method suitable for outdoor positioning to UWB/IMU for indoor positioning, for example.



(a) C/No for first trip

(b) C/No for second trip



(c) Maximum available satellites for first trip

(d) Maximum available satellites for second trip

Figure 3: Comparison of C/NO and number of satellites for two test trips on same navigation path

IV. RESULTS ANALYSIS

Accurate detection of the IO transition would lead to the right decision-making in the navigation mode to be employed in seamless positioning. In our studies, we made use of the ML model for indoor-outdoor (IO) detection using an IO signal transition pattern and the available number of satellites. This approach is more reliable than the use of the signal strength of certain sensors embedded in the location system such as a light sensor, Bluetooth, Wi-Fi, magnetometer, or GNSS signal strength. This is because the solutions based on power-hungry sensors, such as Wi-Fi, could be an issue, especially for mobile devices due to limited battery capacity.

We implemented and tested some machine learning algorithms for classification, including Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), Logistic Regression (LR), Naive Bayesian (NB), and Neural Network (NN). The ML models were used to train and classify the detected environment into indoor or outdoor.

From Figure 4, we find that all the algorithms have accuracies better than 70%. Logistic regression (LR), SVC, RF, and DT all perform the best, with an average accuracy of 100%. KNN had an accuracy of 99.35%. The NN performed worst with an accuracy of 70.4%. The confusion matrix for the Näive Bayes algorithm is shown in Table 1.

Table 1: Confusion matrix for NB classifier.

Environment	Open Outdoors	Light Indoors
Open Outdoors	75.84%	24.16%
Light Indoors	4.88%	95.12%

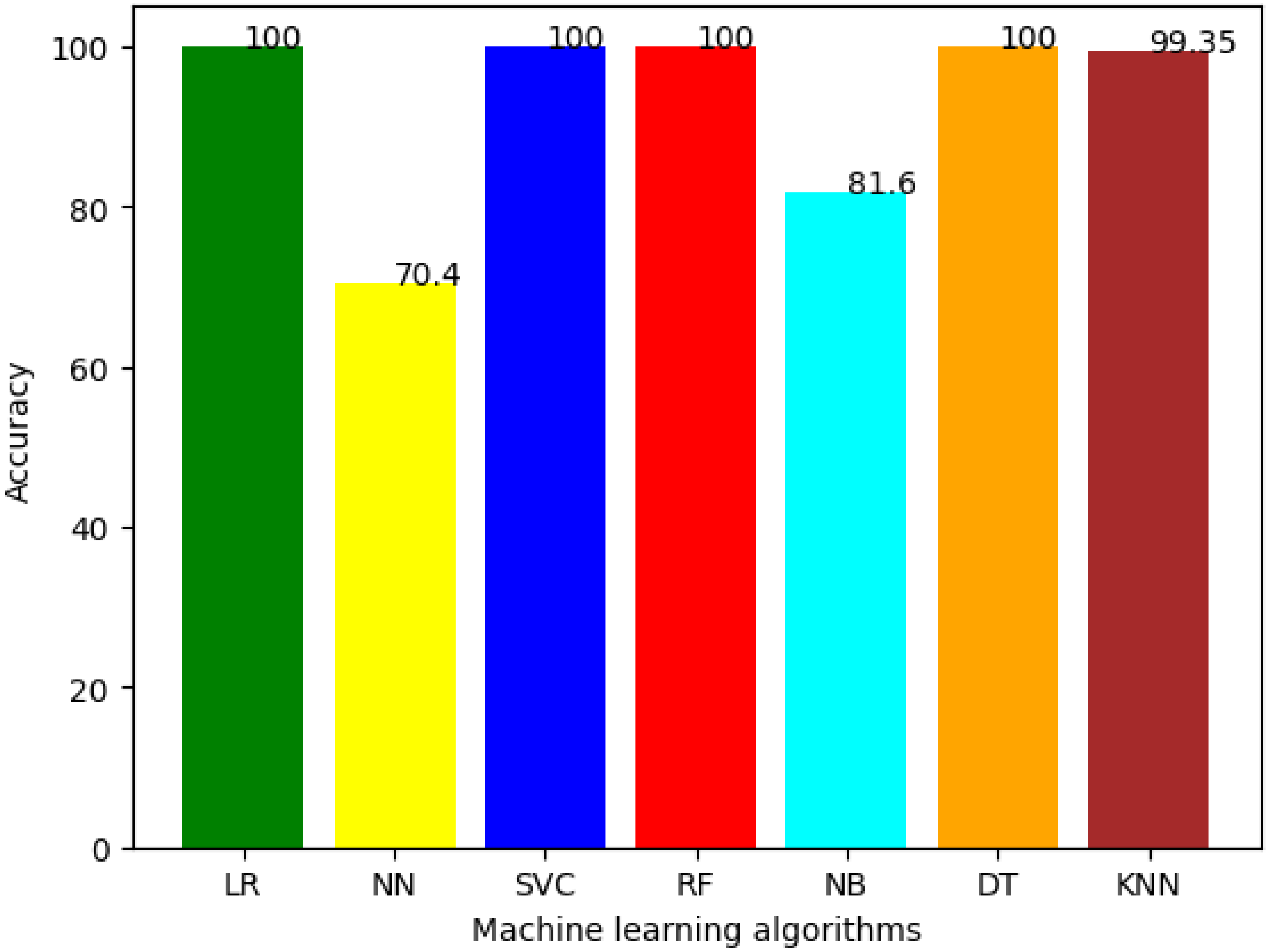


Figure 4: Classification accuracy using different classifiers implemented by different machine learning algorithms.

Table 1 shows that we can detect open outdoor environments correctly. There is a 24.16% possibility of identifying light indoors as open outdoor environments, and a 4.88% possibility of identifying open outdoors as light indoors environments. The LR, SVC, RF, and DT algorithms could distinguish between the open outdoors and light indoors environments more accurately by 100%.

This IO detection method can be useful in the integration of GNSS with UWB/Wi-Fi/IMU systems to achieve seamless navigation for indoor-outdoor positioning. The integration of GNSS with UWB/Wi-Fi/IMU systems can be done using different integration schemes. The positioning method can be selected between, for example, a GNSS/IMU positioning method suitable for outdoor positioning and UWB/IMU for indoor positioning.

Integration schemes: GNSS measurements are easily disturbed by external influences such as multipath, but integrating GNSS with IMU is beneficial as the advantages and disadvantages of GNSS and IMU complement each other to enable accurate measurements in challenging areas. There are three types of integration schemes, namely loosely coupled, tightly coupled, and ultra-tight coupled integration [9].

V. CONCLUSION

Seamless indoor-outdoor positioning remains a challenging aspect for Positioning, Navigation, and Timing (PNT). It is even more complex with variations in the nature of the outdoor (open skies, urban canyons, etc.) and indoor (semi-indoor, deep indoor, etc.) environment. The past decades have seen a variety of navigation techniques being proposed to provide accurate positioning in different environments. Much ongoing research still concentrates on the separate environments as either outdoor or indoor navigation, thereby, lacking to address the difficulties of seamless positioning.

This research seeks to investigate and implement a seamless IO positioning by correct detection of the IO transition and integration of GNSS and indoor technologies (UWB, Wi-Fi, etc.) to provide accurate positioning when transitioning from indoor to outdoor environments. Our implementation of indoor-outdoor (IO) detection strategies makes use of ML to recognize the IO signal transition pattern. We evaluated the IO detection performance and presented the results.

In the future, we propose to continue the process by using the developed IO detection method to perform different integration schemes to combine GNSS with UWB, Wi-Fi, and IMU in one system. We will use the time latency of the transition detection as an important criterion. When the condition is favorable for GNSS (open outdoor), the output positions of the GNSS receiver are used as inputs to the Extended Kalman Filter for GNSS/IMU integration, and when GNSS is degraded (indoors) the system will switch to UWB/Wi-Fi/IMU integration.

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