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Decision Tree-Based Direction Detection Using IMU Data in Autonomous*

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A B S T R A C T

Location detection plays a crucial role in various applications. In this study, a machine learning (ML) method using inertial measurement unit (IMU) data was developed to determine direction with the Global Positioning System (GPS). In this study, an electronic board was designed using an Arduino Mega, Altimu-10 IMU sensor, GPS module, and SD card module. This electronic board was placed on a car to create a new dataset. This dataset consists of 1952x11 data. The dataset was obtained using accelerometer (x, y, z), gyroscope (x, y, z), compass (x, y, z), and GPS sensor data. The Decision Tree Algorithm was proposed for direction determination in this study. The angles between each position and the previous position were calculated using the latitude and longitude values obtained from the collected data. Then, the data were divided into 4 classes: North, East, South, and West, based on specific angle ranges. Finally, a direction detection model was developed using IMU data in the proposed method, achieving an accuracy of approximately 82.11%.

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Otonom Robotlarda IMU Verilerini Kullanan Karar Ağacı Tabanlı Yön Tespiti

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ÖZET

Konum tespiti, birçok uygulama alanında önemli bir role sahiptir. Bu çalışmada, yerel konumlandırma sistemi (GPS) ile yön tespiti yapmak için atalet ölçü birimi (IMU) verilerinin kullanıldığı bir makine öğrenmesi (ML) yöntemi geliştirilmesi amaçlanmıştır. Bu çalışma kapsamında, Arduino Mega, Altimu-10 IMU sensör, GPS modülü ve SD kart modülü kullanılarak bir elektronik kart tasarlanmıştır. Bu elektronik kart, bir otomobil üzerine yerleştirerek yeni bir veri seti oluşturulmuştur. Bu veri seti 1952x11 veriden oluşmaktadır. Bu veri seti ivmeölçer (x, y, z), jiroskop (x, y, z), pusula (x, y, z) ve GPS sensöründen alınan veriler yardımıyla elde edilmiştir. Bu çalışmada yön tespiti için Karar Ağacı Algoritması önerilmiştir. Elde edilen verilerden Enlem ve Boylam değerleriyle her konumun bir önceki konum ile açısı hesaplanmıştır. Daha sonra belirli bir açı aralığına göre Kuzey, Doğu, Güney ve Batı olmak üzere veriler 4 sınıfa ayrılmıştır. En sonunda da IMU verileri önerilen yöntemde kullanılarak yön tespit modeli geliştirilmiş ve yaklaşık %82,11 doğruluk(accuracy) elde edilmiştir.

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1. INTRODUCTION

Location information has always had an important place for people. Because it makes people's daily lives easier and allows them to interact with their environment. Location determination studies start with maps and today extend to GPS systems. With the development of technology and the increasing importance of location information, studies in this field are increasing day by day. Nowadays, the importance of location information has increased with elements such as smart systems, vehicles, and robots that act instead of people, in order to make people's lives easier and reduce risks. Therefore, in unmanned systems, the starting position must be known to move from one place to another. GPS (Global Positioning System) has been a major advancement in being able to share location information. However, location determination should be possible without GPS technology. Because GPS signals may be weak in some places or may not be usable in cases of international disputes since GPS is a satellite-based radio navigation system managed by the US Space Force. This situation poses a significant problem. In order to prevent these problems, methods such as IMU (Inertial Measurement Unit), ZigBee, Bluetooth, Beacon, Wi-Fi, LIDAR, and RFID (Radio frequency identification) have been developed to solve location information problems in robots (Girgensohn, Patel, and Biehl 2024; Khanh et al. 2020; Regus, Talar, and Labudzki 2019). These methods have advantages and disadvantages. ZigBee, Bluetooth, Beacon, Wi-Fi, LIDAR, and RFID systems work depending on the environment (Kaya 2018). These systems, which can detect location depending on the environment, do not work compatible with different environments. At the same time, it is difficult to achieve high performance since ZigBee, Bluetooth, Beacon, Wi-Fi, and RFID systems use wireless technologies.

In the literature, studies are carried out to obtain location information with many technologies without using GPS data. In particular, location information acquisition studies are carried out using methods such as ZigBee, Bluetooth, Beacon, Wi-Fi, LIDAR, and RFID. Literature studies that are similar to the subject of our study are summarized in Table 1.

Table 1. Literature studies that are similar to the subject of the study

References	Year	Purpose of Study
Kaya et al. (Kaya 2018)	2018	In this thesis study; An indoor positioning system is proposed using the received signal strength and acceleration measurements.
Lopez et al. (Álvarez López, de Cos Gómez, and Las-Heras Andrés 2017)	2017	In this study; Two antennas were used and RSSI values were collected by placing RFID tags. Internal location determination was made using the collected data.
Oguntala et al. (Oguntala et al. 2018)	2018	In this study; Real-time location detection technologies for IoT applications are described.
Karabey (Karabey 2015)	2015	In this thesis study; Indoor positioning methods have been proposed using the Wi-Fi-based fingerprint method. In addition to wireless-based indoor positioning methods, multi-sensor-based methods based on inertial data have also been developed.
Xing et al. (Xing et al. 2021)	2021	In this study; A multi-sensor fusion self-positioning system of a miniature underwater robot in structured and GPS-blocked environments is proposed.
Kepper ve diğ. (Iv, Claus, and Kinsey 2019)	2019	In this study; An IMU and acoustic range measurement-based navigation method has been proposed for underwater vehicles.
Poulose et al. (Poulose, Eyobu, and Han 2019)	2019	In this study; Indoor location estimation algorithms have been developed using IMU data obtained from a smartphone.
Farooq et al. (Farooq and Kamal 2019)	2019	In this study, sensor data on smartphones was used for indoor location detection and tracking. The data collected from the sensors was recorded in the database. Its location on the map was determined using the three-axis data and elevation data obtained from the acceleration sensor.
Sanchez et al. (Hernández Sánchez, Fernández Pozo, and Hernández Gómez 2019)	2019	In this study; A deep neural network model is proposed for driver identification using accelerometer signals from smartphones.
Du et al. (Du et al. 2020)	2020	In this study, real-time onboard 3D attitude estimation of unmanned aerial vehicles in multi-environments using multi-sensor data fusion was developed.
Shu et al. (Shu, Chen, and Zhang 2022)	2022	In this study; Efficient image-based indoor positioning was performed with the help of MEMS on the mobile device.
Y. Li et al. (Li et al. 2022)	2022	In this study; A spatiotemporal calibration algorithm has been developed for the IMU-LiDAR navigation system based on the similarity of motion trajectories.
Mahdi et al. (Mahdi et al. 2022)	2022	In this study; A machine learning approach is presented for an advanced inertial navigation system solution.
R. Sun et al. (R. Sun et al. 2022)	2022	In this study; Pseudo-orange error estimation has been made for adaptive tightly coupled GNSS/IMU navigation in urban areas.
Y. Sun et al. (Y. Sun et al. 2022)	2022	In this study; A motion model supported GNSS/MEMS-IMU integrated navigation system has been developed for the land vehicle.
Greff et al. (Greff et al. 2017)	2017	In this study; an LSTM-based odometry design was implemented.
Chen et al. (Chen et al.	2018	In this study; an LSTM-based odometry design was implemented.

2018)		
Wagstaff et al. (Wagstaff and Kelly 2018)	2018	In this study; A zero-speed EKF model is proposed that updates measurements using EKF at a specific time when the LSTM model detects a zero-speed condition.
S. Wang et al. (Wang et al. 2017)	2017	In this study; the LSTM model was developed to extract distinctive features from images to learn the motion between two consecutive frames.

Within the scope of this study, it is aimed to develop a machine-learning method that uses inertial data for location determination in autonomous vehicles. The main focus of our work is; The aim is to produce an electronic system that can be used for location detection, to collect the data set by fixing this system to the car, and to develop and verify the machine learning method. This study contributes to direction determination. In Table 2 below, the tools used in some studies for location determination in the literature are given.

Table 2. Tools used in IMU-Based studies for Location Detection in the literatüre

Reference, Year	Jiroskop	Accelerometer	Compass
Kaya et al. (Kaya 2018), 2018	-	+	-
Xing et al. (Xing et al. 2021), 2021	-	+	-
(Hernández Sánchez et al. 2019), 2019	-	+	-
Shu et al. (Shu et al. 2022), 2022	+	+	+
Kopar et al.(Kopar 2020), 2020	+	+	-
Y. S. Li et al. (Li and Ning 2018), 2018	+	+	-
Orhan YAMAN et al. (Yaman, Tasar, and Yakut 2022), 2022	+	+	+
D. Wang et al. (Wang et al. 2019), 2019	+	+	+
Poulose et al. (Poulose and Han 2019), 2019	+	+	+
Prikhodko et al. (Prikhodko et al. 2018), 2018	+	-	+
Şahin et al. (Şahin and Ulamış 2023), 2022	+	+	-
Okudan et al. (Okudan 2019),	+	+	+
Gögüş et al. (Gögüş 2022), 2022	-	+	-
Ata et al. (Ata 2022), 2022	-	+	-
Our Study, 2024	+	+	+

In Table 2, the tools (gyroscope, accelerometer, and compass) used in some studies for position determination in the literature are given. As seen in the table, in some studies only the gyroscope sensor was used, in some studies the accelerometer sensor or some compass sensors were used. In our study, an electronic card system was created using all of these tools, and IMU and GPS data were obtained. The main purpose of the study is to develop a machine learning classification method that can produce real-time direction data (North, East, South, West) as output by using the IMU and GPS sensor data obtained for direction determination. Thanks to this machine learning method, it can be determined in advance which direction to go depending on the location.

2. MATERIALS AND METHODS

In this study, a system that uses inertial measurement units to determine the location of autonomous vehicles has been developed. In this embedded system, an Altumu-10 sensor was used to collect data such as GPS, Gyro, Accelerometer, and Compass (Magnetometer). Arduino Mega development card was used to read the data from these sensors and log them to the memory card. The architecture of the embedded system developed in this study to collect IMU and GPS data is shown in Figure 1 (Yaman et al. 2022).

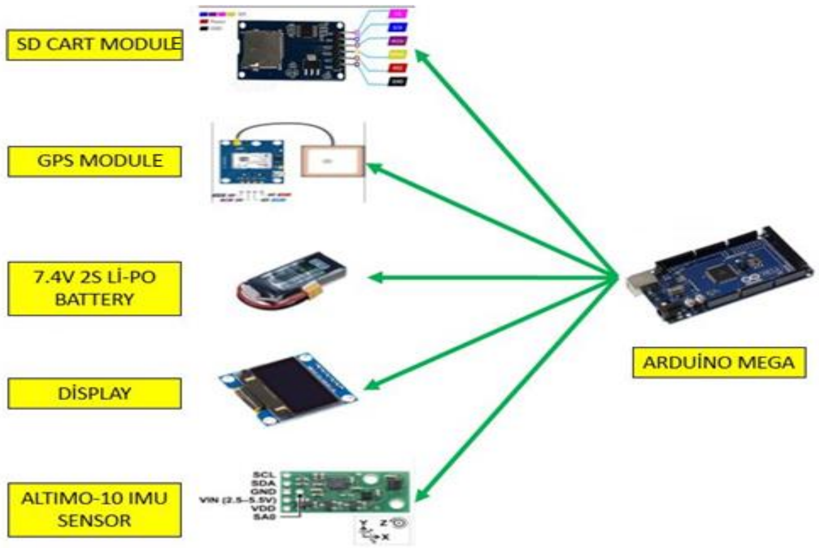

Figure 1. The architecture of the embedded system developed for collecting IMU and GPS data in this study

Data such as location, altitude, Gyro, accelerometer, and compass were collected from the sensors given in Figure 1. Sample data collected with the developed embedded system is shown in Figure 2.

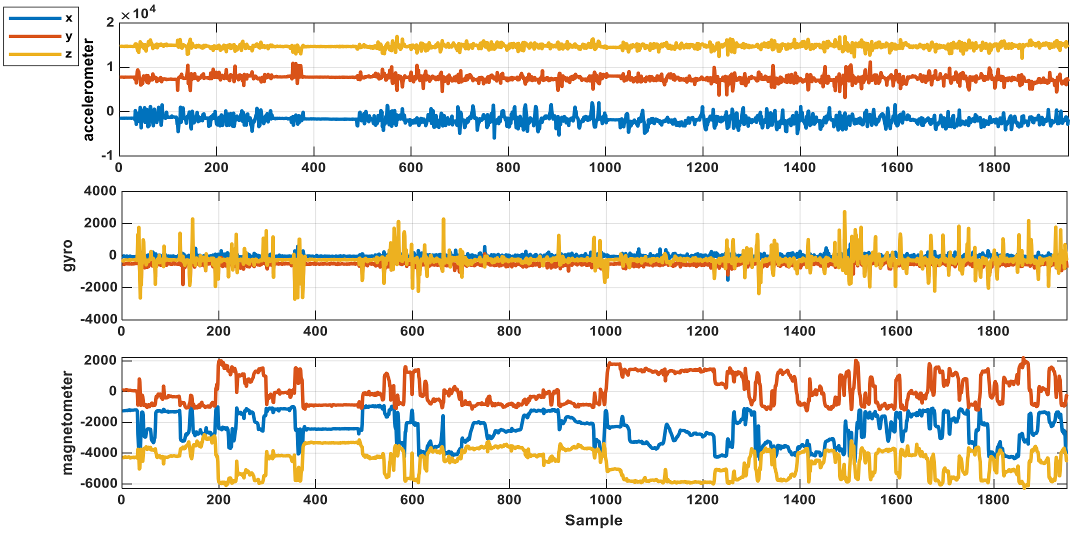

Figure 2. Sample data collected with the developed embedded system

The embedded system developed in this study is fixed on the automobile. The car traveled approximately 50 km/h between 20 km/h and 100 km/h. During the data set collection phase, the movement of the car is shown on the map in Figure 3.

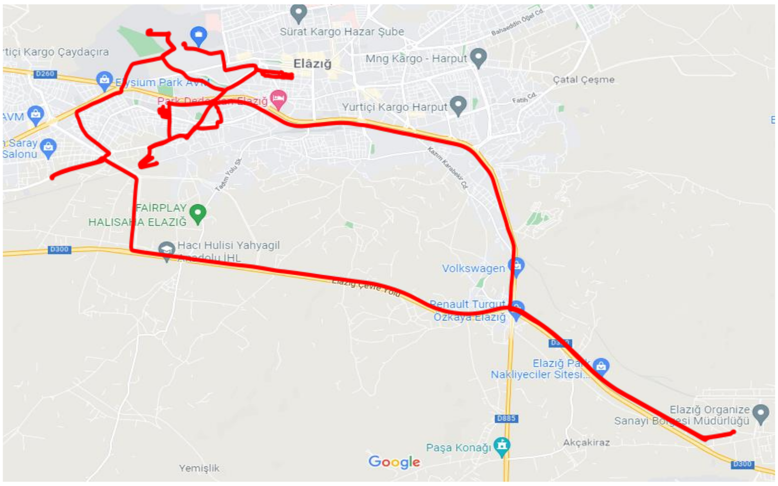

Figure 3. Movement of the car for data set collection

Figure 3 shows the car's route on the map. 1952 samples were collected during the car's journey. Each sample contains accelerometer (x,y,z), gyro (x,y,z), compass (x,y,z), latitude and longitude data. The size of the collected data set is 1952x11.

2.1. Method

The decision Tree Classification Method was applied to this data set. Thanks to the developed methods, it was determined in which position and in which direction the autonomous system was directed by looking at the IMU data. The flow chart of the proposed method is given in Figure 4.

As can be seen in Figure 4, the proposed method consists of six basic steps. First of all, accelerometer (x,y,z), gyro (x,y,z), compass (x,y,z), latitude and longitude data were collected on the developed embedded system. The collected data was parsed and converted into a usable form for classification. For this transformation, Latitude and Longitude values and angle values for each location with the previous location were obtained. Then, the angle values obtained were divided into 4 classes: North, East, South, and West, according to the ranges given in Table 3. Additionally, since the first position is considered the starting position, it does not have an angle value. For this reason, it was not used for the classification process and the number of data decreased to 1951.

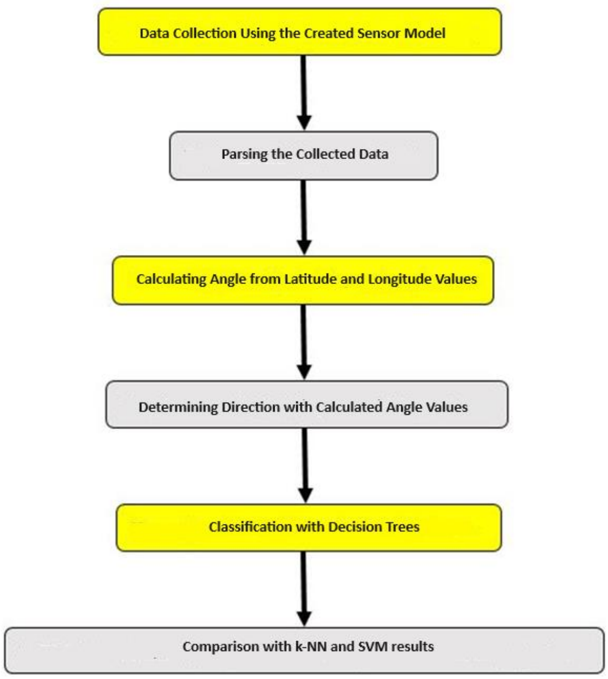

Figure 4. Flow chart of the proposed method

Table 3. Direction determination according to angle range

Class No	Direction	Angle Range
1	North	direction_angle >= 315 ‖ < 45 direction_angle
2	East	direction_angle >= 45 && direction_angle < 135
3	South	direction_angle >= 135 && direction_angle < 225
4	West	direction_angle >= 225 && direction_angle < 315

After the classes were determined, the results were compared using the Decision Tree Classification Method, KNN, and SVM methods to predict the direction classes using accelerometer (x,y,z), gyro (x,y,z), compass (x,y,z) values.

The k-Nearest Neighbor (KNN) algorithm is a supervised machine learning algorithm. In this method, the assumption that similar things are close to each other is valid. It is used for classification and regression (Deng et al. 2016; Naviani 2018; Ulgen 2024).

Steps of k-NN algorithm:

- First, the k parameter is determined. This parameter is the number of nearest neighbors to a given point. For example: let k = 2. In this case, classification will be made according to the 2 closest neighbors.
- The distance of the new data to be added to the data set, relative to the existing data, is calculated one by one with the help of relevant distance functions.
- The k nearest neighbors from the relevant distances are considered. It is assigned to k neighbors or classes of neighbors according to their attribute values.
- The selected class is considered as the class of the observation value expected to be predicted. So the new data is labeled.
- Support Vector Machine (SVM) is a machine learning algorithm used in classification and regression problems. The main goal of SVM is to find a hyperplane that best separates samples belonging to different classes (Baygin, Baygin, and Karakose 2019).

Steps of SVM Algorithm:

- <u>Data collection and preprocessing</u>: Before starting the training of the SVM, the data set to be classified must be collected and preprocessing steps must be carried out. In this step, the data set is examined, missing data is filled in if necessary, outliers are identified, and features are normalized.
- <u>Feature selection</u>: In order for SVM to work on the data set, appropriate features must be selected. In this step, features that are important and improve classification performance are identified.
- <u>Creating feature vectors</u>: Each data sample should be represented as a vector of features. Feature vectors are created for each example of the data set to be classified.
- <u>Determination of training data and labels</u>: For training the SVM, it is necessary to determine the input data and the labels showing which class this data belongs to. The training dataset consists of feature vectors and corresponding class labels.
- <u>Training of the SVM model</u>: The SVM model is trained using the training data and labels. SVM is optimized to find a hyperplane that separates different classes in the data set. In this step, the parameters of the SVM are determined and the training algorithm is run.
- <u>Validation of the model</u>: Validation data is used to evaluate the performance of the trained SVM model. The accuracy of the model is evaluated using the error matrix or other performance metrics.
- <u>Tuning and optimization of the model</u>: Parameters and hyperparameters of the SVM can be tuned to improve the performance of the model. In this step, different parameter values are tested and the model is optimized.

- Classification of new examples: The trained SVM model can be used to predict classes of new, unclassified examples. In this step, feature vectors of new samples are created and classification is made using the SVM model.

SVM is an effective algorithm used in classification problems, and the above steps generally reflect the application process of SVM.

A decision tree uses features (independent variables) in the dataset to predict a target variable (Rajesh, Sai Vardhan, and Sujihelen 2020).

Steps of the Decision Trees Method:

- Before starting the decision tree analysis, it is necessary to determine the first node, the root node. The root node is the first point from which the target variable will be predicted.
- The decision tree makes a split on one feature at each node. A partition divides the data set into subsets and these subsets are aimed to be homogeneous. The best split is the one that provides the greatest information gain.
- Once the best split is selected, the data set is divided into subsets based on this split. Each subset creates a child node.
- Once the child nodes are created, the same steps are repeated for each subset. On each subset, a split is selected, the split is applied, and new child nodes are created.
- A stopping condition should be set to control the size and depth of the decision tree. When the stopping condition is met, the tree-creation process ends.
- When the above steps are repeated, the decision tree is completed and a hierarchical structure is created. This tree is used to predict the target variable based on the values of features in the dataset.
- Once the tree is created, pruning can be applied to remove unnecessary branches or simplify the tree. Pruning helps prevent the tree from overfitting and increases its generalization ability.

3. EXPERIMENT RESULTS AND DISCUSSION

In this study, MATLAB Classification Learner Toolbox was used to obtain classification results. KNN, SVM, and Decision Tree methods were preferred for classification. 10-fold cross-validation was used for validation in each method. The confusion matrix results obtained for the methods used are presented in Figure 5.

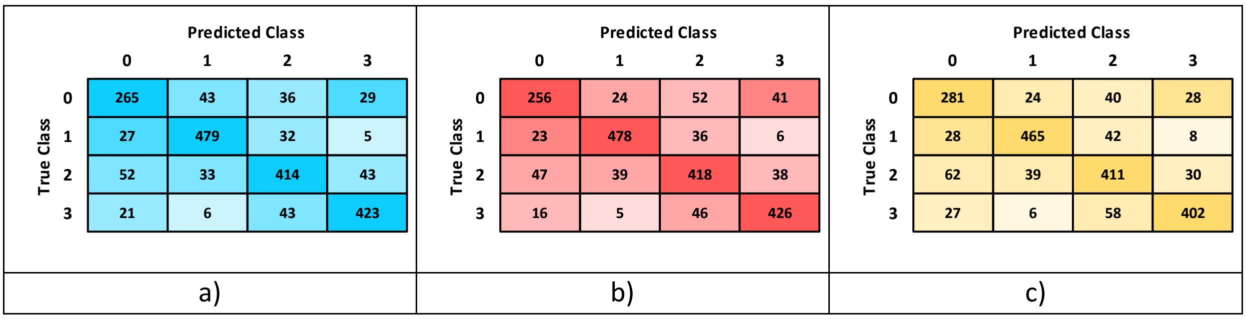

Figure 5. Confusion matrix a) Decision Trees b) k-NN c) SVM

When the results calculated for the three methods are examined in Fig. 5, it can be seen that the best direction prediction results are generally calculated in the Decision Tree Algorithm. Class-based accuracy rates of the proposed method are given in Figure 6.

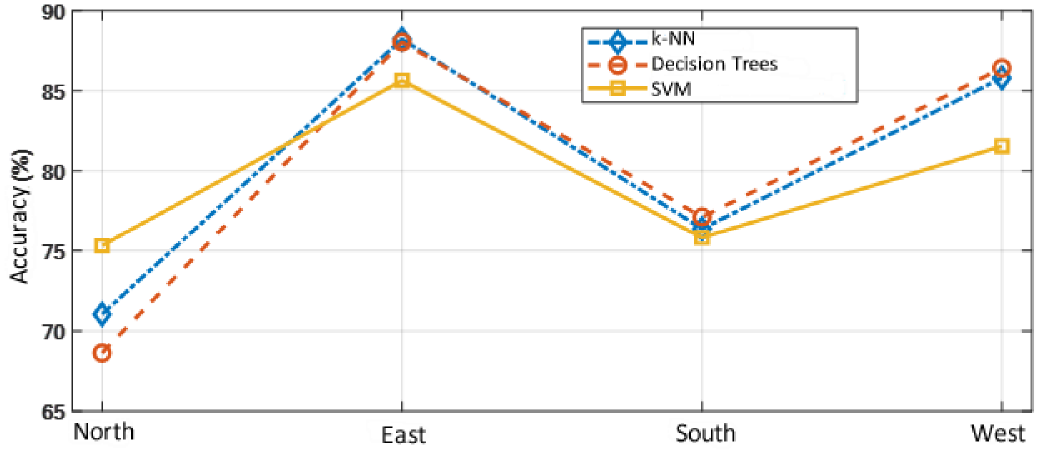

Figure 6. Class-based accuracy rates

The proposed method was run for 1000 iterations and Accuracy, Precision, Recall, Geometric Mean, and F1-Score results was calculated. The calculated results are shown in Table 4.

Table 4. 1000 iteration performance values of the proposed method

		Accuracy (%)	Precision (%)	Recall (%)	Geometric Mean (%)	F1-Score (%)
Decision Trees	**Max**	**82.11**	**81.47**	**81.33**	**81.04**	**81.40**
	Min	79.80	79.12	79.16	78.90	79.14
	Mean	81.06	80.50	80.38	80.13	80.44
	Std	0.31	0.32	0.31	0.32	0.31
k-NN	**Max**	81.65	81.15	80.90	80.56	81.02
	Min	79.49	78.79	78.60	78.10	78.74
	Mean	80.52	79.97	79.69	79.31	79.83
	Std	0.33	0.36	0.35	0.37	0.35
SVM	**Max**	80.88	80.48	80.49	80.37	80.48
	Min	78.88	78.42	78.36	78.18	78.39
	Mean	79.98	79.62	79.56	79.44	79.59
	Std	0.43	0.44	0.46	0.47	0.45

Table 4 shows that the best result was obtained with the Decision Trees Algorithm.

4.CONCLUSION

With today's technology, we can remotely control autonomous vehicles and monitor their movements in real-time. Using GPS modules, the location information of autonomous vehicles can be connected to more than one satellite, and location determination can be made with high accuracy. But sometimes problems occur due to reasons such as GPS signals not being received. That's why we're looking for new methods. In this study, an embedded system was developed and data was collected in the external environment by fixing it on the automobile. GPS data showing the location of the car was also recorded during the data collected. From the collected data, latitude and longitude data were calculated and the angle between each location and the previous location was calculated and labeled in four classes North, East, South, and West. Then, an attempt was made to develop a direction prediction model using IMU data.

K-Nearest Neighbor, Support Vector Machine, and Decision Tree classification Algorithms were applied to these data. 82.11% Accuracy was calculated with the proposed method Decision Tree Algorithm. The decision Tree Algorithm was compared with other classification methods and it was seen that the proposed method was successful.

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