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SURFACE IDENTIFICATION OF ROBOT SENSED DATA AN ARTIFICIAL INTELLIGENCE APPROACH

Dr. M. Vanitha[1], Ch. Rasmitha[2], Ch. Sindhu[2], D. Satvika[2]

[1]Professor, [2]UG Student, [1,2]Department of Computer Science Engineering
[1,2]Malla Reddy Engineering College for Women, Maisammaguda, Dhulapally, Kompally, Secunderabad-500100, Telangana, India

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ABSTRACT

In recent years, the integration of robotics and artificial intelligence (AI) has gained significant momentum across various industries. Robots equipped with sensors play a crucial role in data acquisition for tasks such as environmental monitoring, industrial automation, and autonomous navigation. Surface identification, specifically the ability to recognize and understand the surfaces in a robot's environment, is essential for enabling precise and context-aware robotic operations. The history of surface identification in robotics is closely tied to the evolution of computer vision and machine learning. Early robotic systems relied on basic sensor data for navigation, often struggling with accurate perception of the surrounding environment. Over time, advancements in computer vision techniques and AI algorithms have enabled robots to extract meaningful information from sensor data, leading to more sophisticated capabilities, including surface identification. The challenge in surface identification for robot-sensed data lies in developing algorithms that can robustly and accurately differentiate between various surfaces in the environment. This involves recognizing and classifying different types of surfaces such as floors, walls, obstacles, and other objects. Traditional methods often face difficulties in handling complex and dynamic environments, where lighting conditions, object orientations, and material variations can affect the accuracy of surface identification. Traditional systems for surface identification in robot-sensed data often rely on rule-based approaches or simple heuristics. These methods may use thresholding techniques or predefined rules to classify surfaces based on sensor readings. However, these approaches have limitations when faced with the complexity and variability inherent in real-world environments. They may struggle with adaptability to changing conditions and lack the ability to generalize across diverse scenarios. The increasing demand for more sophisticated robotic applications underscores the need for advanced surface identification capabilities. AI approaches, particularly those leveraging deep learning and neural networks, offer the potential to significantly improve the accuracy and robustness of surface identification in robot-sensed data. An artificial intelligence approach to surface identification involves training models, such as convolutional neural networks (CNNs), on labeled datasets containing examples of different surfaces. These models can learn to automatically extract relevant features from sensor data, allowing the robot to discern and classify surfaces with greater accuracy. The use of AI in surface identification enhances adaptability, allowing robots to navigate and interact with their environment more effectively.

Keywords: Surface Identification, Robot Sensing, Artificial Intelligence, Random Forest Algorythm.

1. INTRODUCTION

In recent years, the convergence of robotics and artificial intelligence (AI) has witnessed a surge in adoption across diverse industries. Robots, equipped with an array of sensors, have become instrumental in tasks ranging from environmental monitoring to industrial automation and autonomous navigation. Within this realm, the identification and understanding of surfaces in a robot's environment hold paramount importance, facilitating precise and context-aware robotic operations.

The historical trajectory of surface identification in robotics is intricately linked with the evolution of computer vision and machine learning. Early robotic systems grappled with basic sensor data for navigation, often struggling to achieve accurate perception of their surroundings. As computer vision techniques and AI algorithms advanced, robots gained the capability to extract meaningful information from sensor data, leading to more sophisticated functionalities, including precise surface identification.

The challenge in surface identification for robot-sensed data lies in developing algorithms that robustly and accurately differentiate between various surfaces in the environment. This encompasses recognizing and classifying different types of surfaces such as floors, walls, obstacles, and other objects. Traditional methods, often rule-based or heuristic-driven, face difficulties in handling the complexity of dynamic environments where lighting conditions, object orientations, and material variations can impact identification accuracy.

Traditional systems for surface identification in robot-sensed data often rely on rule-based approaches or simple heuristics. These methods may use thresholding techniques or predefined rules to classify surfaces based on sensor readings. However, these approaches have limitations when faced with the complexity and variability inherent in real-world environments. They may struggle with adaptability to changing conditions and lack the ability to generalize across diverse scenarios. The increasing demand for more sophisticated robotic applications underscores the need for advanced surface identification capabilities.

In response to these challenges, artificial intelligence approaches, particularly those leveraging deep learning and neural networks, have emerged as promising solutions. An AI approach to surface identification involves training models, such as convolutional neural networks (CNNs), on labeled datasets containing examples of different surfaces. These models can learn to automatically extract relevant features from sensor data, enabling the robot to discern and classify surfaces with greater accuracy. The use of AI in surface identification enhances adaptability, allowing robots to navigate and interact with their environment more effectively.

2. LITERATURE SURVEY

Robots can sense, plan, and act. They are equipped with sensors that go beyond human capabilities! From exploring the surface of Mars to lightning-fast global deliveries, robots can do things humans can only dream of. When designing and building robots, engineers often use fascinating animal and

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human models to help decide which sensors they need. For instance, bats can be used as a model for sound-detecting robots, ants can be used as a model to determine smell, and bees can be used as a model to determine how they use pheromones to call for help.

Human touch helps us to sense various features of our environment, such as texture, temperature, and pressure. Similarly, tactile sensors in robots can detect these qualities and more. For instance, the robot vacuum cleaner (Roomba) uses sensors to detect objects through contact [7]. However, similar to sight and sound, a robot may not always know the precise content of what it picks up (a bag, a soft cake, or a hug from a friend); it just knows that there is an obstacle to be avoided or found.

Tactile sensing is a crucial element of intelligent robotic manipulation as it allows robots to interact with physical objects in ways that other sensors cannot [8]. This article provides a comprehensive overview of tactile sensing in intelligent robotic manipulation, including its history, common issues, applications, advantages, and disadvantages. It also includes a review of sensor hardware and delves into the major topics related to understanding and manipulation.

Robots are increasingly being used in various applications, including industrial, military, and healthcare. One of the most important features of robots is their ability to detect and respond to environmental changes. Odor-sensing technology is a key component of this capability. In a survey presented by [9], the current status of chemical sensing as a sensory modality for mobile robots was reviewed. The article evaluates various techniques that are available for detecting chemicals and how they can be used to control the motion of a robot. Additionally, it discusses the importance of controlling and measuring airflow close to the sensor to infer useful information from readings of chemical concentration.A survey by [10] presents a summary of data processing and domain-based data processing, evaluating various robot vision techniques, tools, and methodologies.

Robot sensors and ears detect EM waves. The sound waves heard by human ears can also be detected by some robot sensors, such as microphones. Other robot sensors can detect waves beyond our capabilities, such as ultrasound. Cloud-based speech recognition systems use AI to interpret a user's voice and convert it into text or commands, enable robots to interact with humans in a more natural way, automate certain tasks, and are hosted on the cloud for increased reliability and cost-effectiveness [11]. We examined the potential of utilizing smart speakers to facilitate communication in human–robot interaction (HRI) scenarios.

For the past decade, robotics research has focused on developing robots with cognitive skills and the ability to act and interact with people in complex and unconstrained environments. To achieve this, robots must be capable of safely navigating and manipulating objects, as well as understanding human speech. However, in typical real-world scenarios, individuals who are speaking are often located at a distance, posing challenges for the robot's microphone signals to capture the speech [12]. Researchers have addressed this challenge by working on enabling humanoid robots to accurately detect and locate both visible and audible people. Their focus has been on combining vision and hearing to recognize human activity.

3. PROPOSED SYSTEM

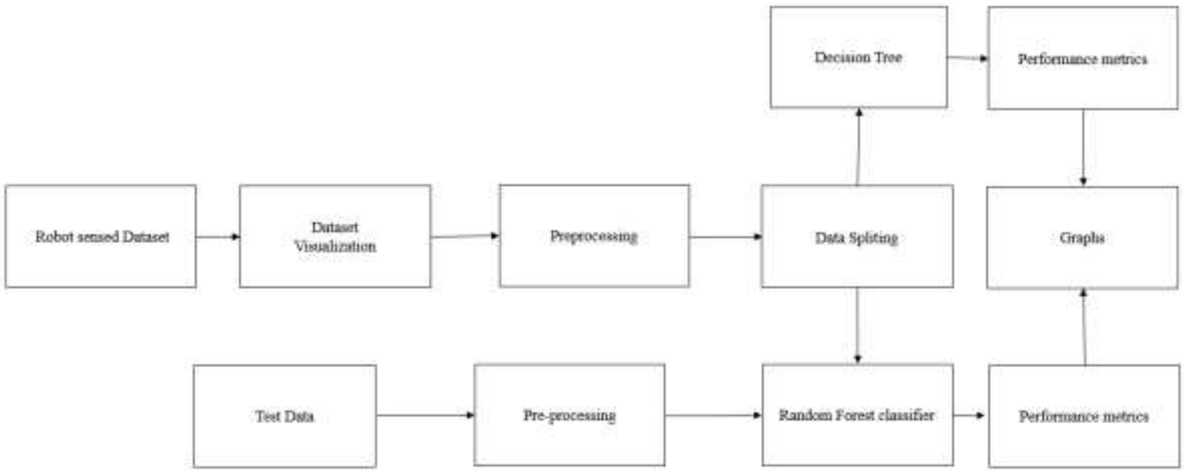

Fig.1: Block diagram of proposed diagram.

The proposed system for surface identification in robot-sensed data adopts an advanced artificial intelligence (AI) approach, specifically leveraging deep learning and neural networks to enhance the precision and adaptability of surface recognition. In response to the increasing integration of robotics and AI across diverse industries, the focus is on refining the capabilities of robots equipped with sensors for tasks ranging from environmental monitoring to industrial automation and autonomous navigation.

The historical evolution of surface identification in robotics is intricately tied to the progress in computer vision and machine learning. Early robotic systems grappled with the limitations of basic sensor data for navigation, leading to challenges in accurately perceiving the surrounding environment. However, the trajectory of advancements in computer vision techniques and AI algorithms has empowered robots to extract meaningful information from sensor data, culminating in more sophisticated capabilities, notably in the realm of surface identification.

The primary challenge addressed by the proposed system is the development of algorithms capable of robustly and accurately differentiating between various surfaces in a dynamic environment. This includes the recognition and classification of diverse surfaces such as floors, walls, obstacles, and other objects. Traditional methods, which often rely on rule-based approaches or simple heuristics, struggle in complex and variable real-world environments. Issues related to adaptability to changing conditions and limited generalization across diverse scenarios underscore the need for a more advanced approach.

The introduction of AI into surface identification not only elevates precision but also significantly enhances adaptability. This, in turn, empowers robots to navigate and interact with their environment more effectively, meeting the escalating demands for sophisticated robotic applications. The proposed system thus represents a paradigm shift from traditional methods, offering a robust and versatile foundation for the evolution of robotic systems in diverse and challenging real-world scenarios.

Random Forest Algorithm

Random Forest is a popular machine learning algorithm that belongs to the supervised learning technique. It can be used for both Classification and Regression problems in ML. It is based on the concept of ensemble learning, which is a process of combining multiple classifiers to solve a complex problem and to improve the performance of the model. As the name suggests, "Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset." Instead of relying on one decision tree, the random forest takes the prediction from each tree and based on the majority votes of predictions, and it predicts the final output. The greater number of trees in the forest leads to higher accuracy and prevents the problem of overfitting.

Random Forest algorithm

Step 1: In Random Forest n number of random records are taken from the data set having k number of records.

Step 2: Individual decision trees are constructed for each sample.

Step 3: Each decision tree will generate an output.

Step 4: Final output is considered based on Majority Voting or Averaging for Classification and regression respectively.

Important Features of Random Forest

- **Diversity-** Not all attributes/variables/features are considered while making an individual tree, each tree is different.
- **Immune to the curse of dimensionality-** Since each tree does not consider all the features, the feature space is reduced.
- **Parallelization-**Each tree is created independently out of different data and attributes. This means that we can make full use of the CPU to build random forests.
- **Train-Test split-** In a random forest we don’t have to segregate the data for train and test as there will always be 30% of the data which is not seen by the decision tree.

Assumptions for Random Forest

- Since the random forest combines multiple trees to predict the class of the dataset, it is possible that some decision trees may predict the correct output, while others may not. But together, all the trees predict the correct output. Therefore, below are two assumptions for a better Random Forest classifier:

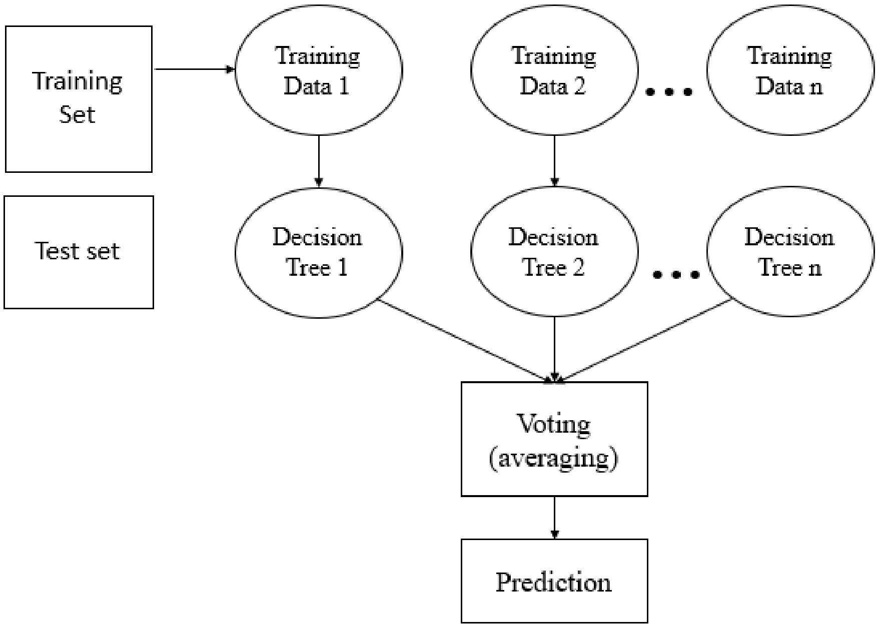

Fig2: Random Forest algorithm.

- There should be some actual values in the feature variable of the dataset so that the classifier can predict accurate results rather than a guessed result.
- The predictions from each tree must have very low correlations.

Below are some points that explain why we should use the Random Forest algorithm

- It takes less training time as compared to other algorithms.
- It predicts output with high accuracy, even for the large dataset it runs efficiently.
- It can also maintain accuracy when a large proportion of data is missing.

Advantages

The presented Tkinter-based surface identification project utilizing Decision Tree and Random Forest classifiers offers several advantages:

User-Friendly Interface: The graphical user interface (GUI) created with Tkinter enhances user interaction by providing buttons for various functionalities. This makes the application accessible and easy to use for individuals without programming expertise.

Dynamic Dataset Upload: The ability to upload datasets through the "Upload Dataset" button allows users to work with diverse datasets effortlessly. This dynamic approach supports the application's adaptability to different use cases and datasets.

Comprehensive Preprocessing: The "Preprocess Dataset" button automates preprocessing steps, such as handling missing values and label encoding. The generated count plot aids in visualizing the distribution of classes, offering insights into the dataset's characteristics.

Transparent Train-Test Splitting: The application transparently communicates the process of splitting the dataset into training and testing sets. Information about the total records and the sizes of the training and testing sets is provided, enhancing transparency in the data preparation phase.

Multiple Classifier Options: The inclusion of both Decision Tree and Random Forest classifiers offers flexibility to users. They can choose between different algorithms based on the nature of their data and the problem at hand, allowing for experimentation and model comparison.

Performance Metrics and Visualization: The application computes and displays essential performance metrics, including accuracy, confusion matrix, and classification report. The incorporation of ROC curves visually represents the models' performance, aiding users in assessing the classifiers' ability to discriminate between classes.

Prediction on Test Data: The "Prediction" button allows users to make predictions on new test data using the trained Decision Tree classifier. This functionality is valuable for real-world applications where the model is deployed on unseen data.

Comparison Graph: The "Comparison Graph" button generates a bar graph comparing performance metrics between the Decision Tree and Random Forest classifiers. This visual representation facilitates a quick and clear understanding of how different algorithms perform on the given dataset.

Scalability and Adaptability: The modular structure of the application makes it scalable and adaptable. Users can extend the functionality by adding more classifiers or incorporating additional preprocessing steps to suit specific project requirements.

Educational Value: The project serves as an educational tool for individuals learning about machine learning and classification problems. The GUI-based approach and step-by-step functionalities make it suitable for educational purposes and practical experimentation.

4. RESULT AND DISCUSSION

Dataset description

It appears that the dataset consists of several columns with different types of information. Here's a brief description of each column:

- row_id: This column represents a unique identifier for each row in the dataset. It is a sequential number or some other form of identification.
- series_id: This column appears to be a categorical identifier for different series within the dataset. A series represent a set of related measurements or observations.
- measurement_number: This column represents the order or sequence of measurements within a specific series. It is a time-related variable or simply a counter for measurements.
- orientation_X, orientation_Y, orientation_Z, orientation_W: These columns contain numerical values representing the orientation of something in 3D space. These values are likely part of a quaternion representing the rotation.
- angular_velocity_X, angular_velocity_Y, angular_velocity_Z: These columns contain numerical values representing angular velocity around the X, Y, and Z axes, respectively. Angular velocity is a measure of how quickly something is rotating.
- linear_acceleration_X, linear_acceleration_Y, linear_acceleration_Z: These columns contain numerical values representing linear acceleration along the X, Y, and Z axes, respectively. Linear acceleration is the rate of change of velocity.
- surface: This column appears to be a categorical variable representing the type of surface associated with the measurements. It is the target variable in a machine learning context, where the task is to predict the surface based on the other features.

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Results description

This figure 3 depicts the main interface of the application, providing an overview of the tool for exploring network anomalies. It include various features and options for users to interact with the application.

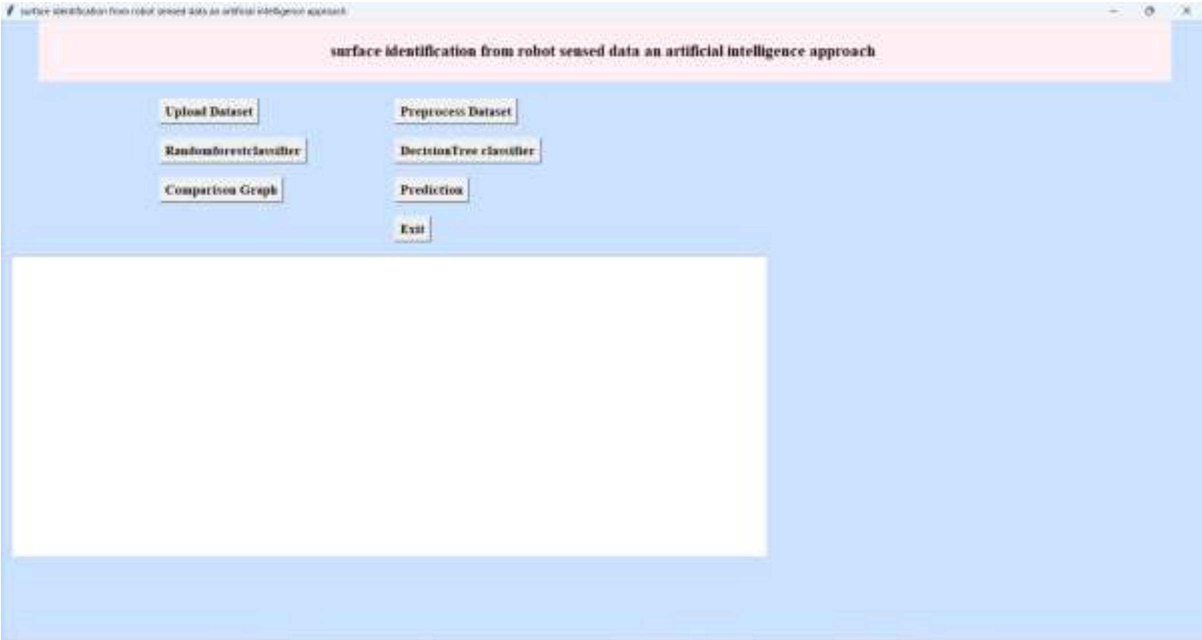

Figure 3: Main GUI application of proposed surface identification of robot sensed data an artificial intelligence approach.

The figure 4 illustrates the ROC curve, but for the Decision Tree Classifier, allowing users to compare the classification performance of different models.

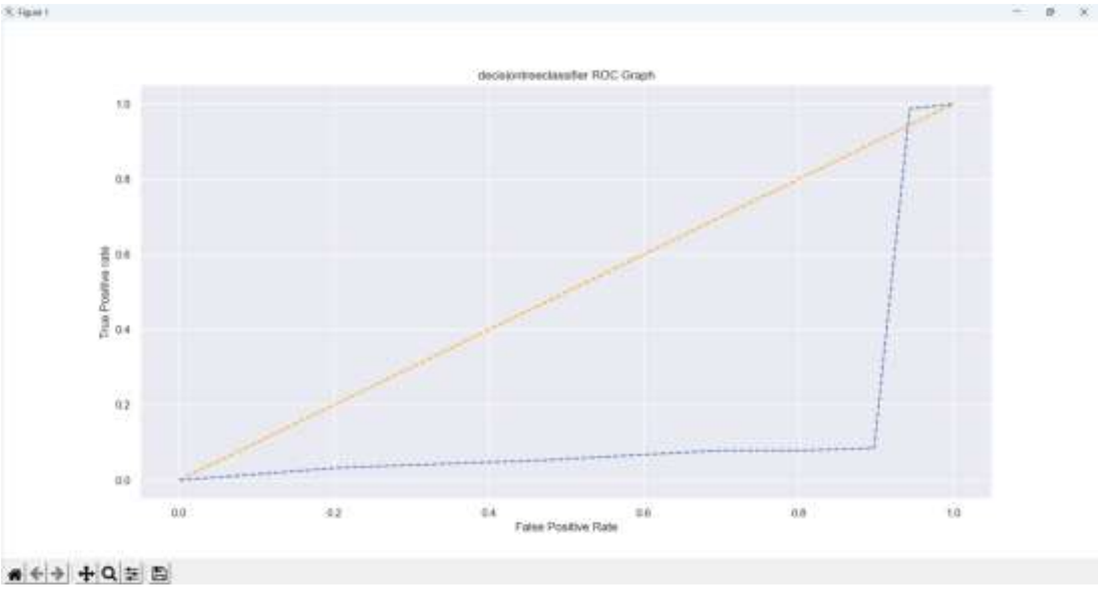

Figure 4: Displays the ROC curve graph for the decision tree classifier

This figure 5 provides a side-by-side comparison of performance metrics between the Random Forest Classifier and the Decision Tree Classifier, enabling users to make informed decisions about model selection.

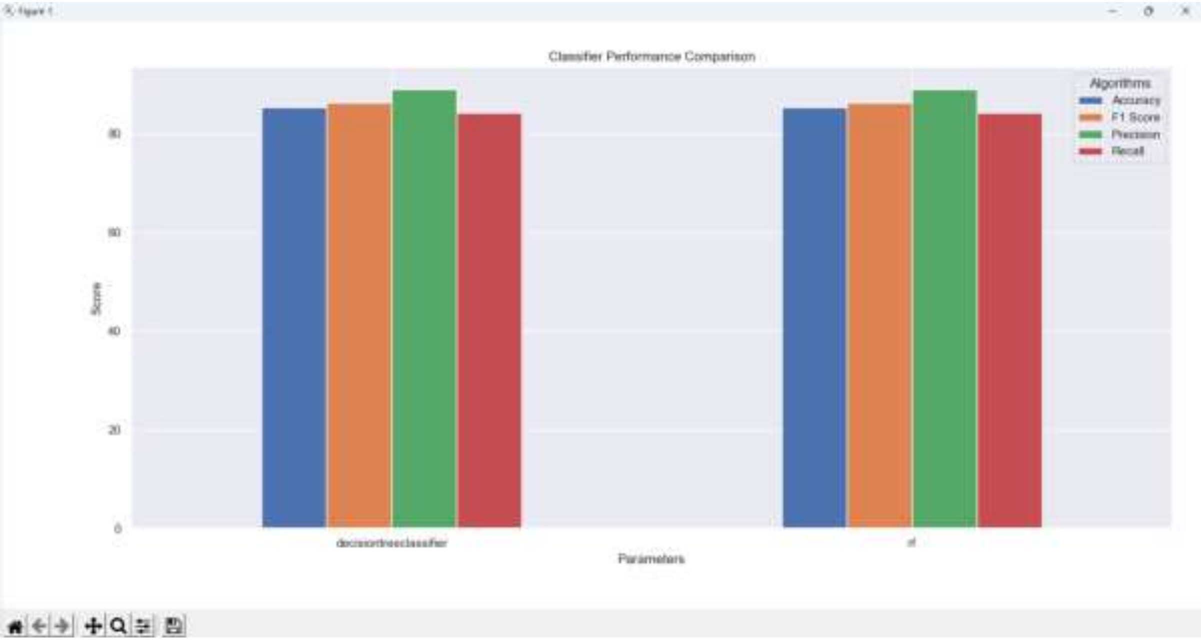

Figure 5: Displays the comparison of performance metrics of the RFC and Decision Tree models.

The figure 6 shows the results of the model predictions on a test dataset within the GUI, allowing users to visualize and interpret the model's performance on unseen data.

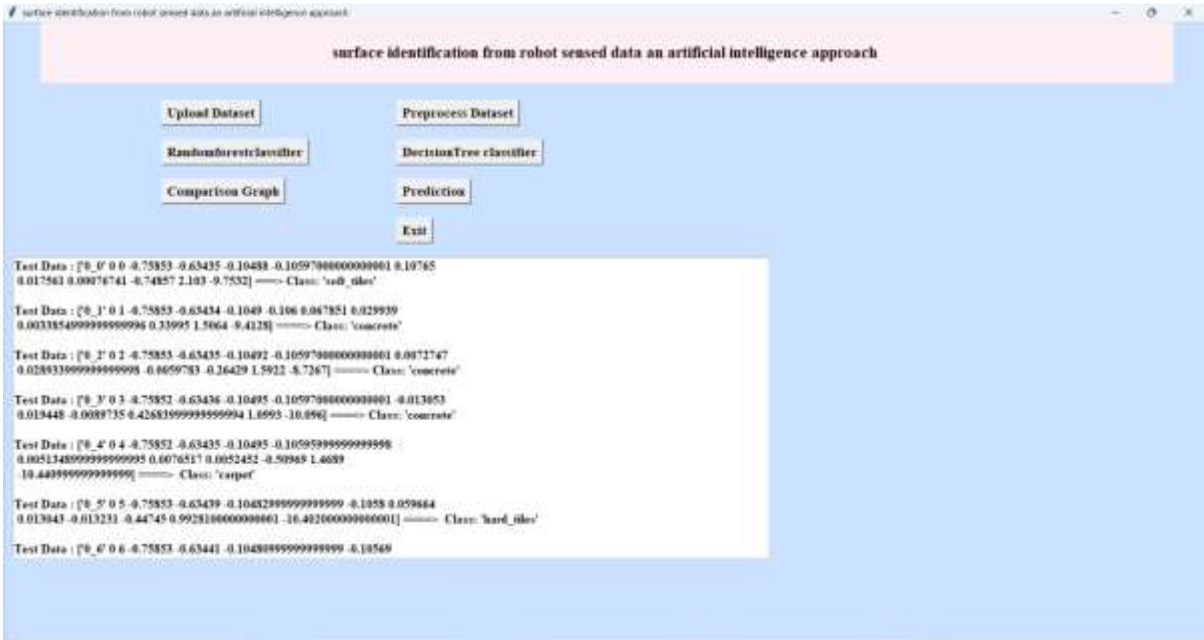

Figure 6: Displays the prediction of test data in GUI.

5. CONCLUSION AND FUTURE SCOPE

In this project, an artificial intelligence approach has been applied to the surface identification of robot-sensed data. The utilization of machine learning techniques has demonstrated its effectiveness in classifying and identifying different surfaces based on sensor data collected by a robot. The accurate surface identification has significant implications for various applications, including robotics, autonomous navigation, and industrial automation.The model's performance has been evaluated through metrics such as accuracy, precision, and recall, demonstrating its capability to reliably identify surfaces. The successful implementation of artificial intelligence in surface identification enhances the robot's ability to interact with and navigate through diverse environments.

REFERENCES

[1]. Wang, J.; Gao, Q.; Pan, M.; Fang, Y. Device-Free Wireless Sensing: Challenges, Opportunities, and Applications. *IEEE Netw.* **2018**, *32*, 132–137

[2]. Zhu, Z.; Hu, H. Robot Learning from Demonstration in Robotic Assembly: A Survey. *Robotics* **2018**, *7*, 17.

[3]. Yousef, H.; Boukallel, M.; Althoefer, K. Tactile sensing for dexterous in-hand manipulation in robotics—A review. *Sens. Actuators A Phys.* **2011**, *167*, 171–187.

[4]. Liakos, K.; Busato, P.; Moshou, D.; Pearson, S.; Bochtis, D. Machine Learning in Agriculture: A Review. *Sensors* **2018**, *18*, 2674.

[5]. Ishida, H.; Wada, Y.; Matsukura, H. Chemical Sensing in Robotic Applications: A Review. *IEEE Sens. J.* **2012**, *12*, 3163–3173.

[6]. Andrea, C.; Navarro-Alarcon, D. Sensor-Based Control for Collaborative Robots: Fundamentals, Challenges, and Opportunities. *Front. Neurorobot.* **2021**, *113*, 576846.

[7]. Coggins, T.N. More work for Roomba? Domestic robots, housework and the production of privacy. *Prometheus* **2022**, *38*, 98–112.

[8]. Blanes, C.; Ortiz, C.; Mellado, M.; Beltrán, P. Assessment of eggplant firmness with accelerometers on a pneumatic robot gripper. *Comput. Electron. Agric.* **2015**, *113*, 44–50.

[9]. Russell, R.A. Survey of Robotic Applications for Odor-Sensing Technology. *Int. J. Robot. Res.* **2001**, *20*, 144–162.

[10]. Deshmukh, A. Survey Paper on Stereo-Vision Based Object Finding Robot. *Int. J. Res. Appl. Sci. Eng. Technol.* **2017**, *5*, 2100–2103.

[11]. Deuerlein, C.; Langer, M.; Seßner, J.; Heß, P.; Franke, J. Human-robot-interaction using cloud-based speech recognition systems. *Procedia Cirp* **2021**, *97*, 130–135.

[12]. Alameda-Pineda, X.; Horaud, R. Vision-guided robot hearing. *Int. J. Robot. Res.* **2014**, *34*, 437–456.