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Machine Learning-Based Mobility-Aware Classification for Satellite Communication Systems

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ABSTRACT

Satellite communication plays a pivotal role in enabling global connectivity by transmitting data, voice, and multimedia content through satellites positioned in various orbital paths. These satellites, traveling at velocities between 7,000 and 28,000 km/h depending on their altitude, follow specific trajectories such as geostationary, polar, and elliptical orbits. Each orbit allows the satellite to cover expansive areas of the Earth, ensuring consistent and uninterrupted communication services essential for telecommunications, navigation, and Earth observation. However, conventional satellite communication systems often depend on fixed models and static algorithms, which are not well-suited to dynamic and rapidly changing mobility conditions. One of the significant challenges lies in the inaccurate prediction of mobility patterns, which leads to increased transmission errors, inefficient coverage forecasting, and suboptimal network resource utilization. To overcome these limitations, the proposed system integrates machine learning techniques to analyze and improve satellite mobility predictions. By leveraging a dataset comprising parameters such as satellite speed, orbital trajectory, signal strength, and coverage area, the system is designed to uncover hidden patterns and enhance the allocation of communication resources. The approach involves a structured machine learning pipeline, including data preprocessing, feature selection, classification algorithms, and model training. Various classification techniques including decision trees, support vector machines (SVM), and deep learning models are employed to enhance the accuracy of satellite movement prediction. The resulting classification of mobility patterns enables more precise trajectory adjustments and contributes to the overall optimization of satellite network performance.

Keywords:
Satellite Communication, Machine Learning, Mobility Pattern Classification, Orbital Trajectory Prediction, Signal Optimization, Decision Trees, Support Vector Machines, Deep Learning, Adaptive Algorithms, Satellite Network Optimization.

1. INTRODUCTION

Geostationary Earth Orbit (GEO) satellites serve as the cornerstone of modern satellite communication systems, offering persistent coverage over fixed regions of the Earth. Positioned approximately 35,786 kilometres above the equator, these satellites orbit at the same rotational speed as the Earth, allowing them to remain stationary relative to a specific geographic location. This unique characteristic makes GEO satellites particularly well-suited for a range of continuous-service applications, including weather forecasting, television broadcasting, and broadband internet delivery.

Unlike satellites in Low Earth Orbit (LEO) or Medium Earth Orbit (MEO), which move rapidly relative to the Earth's surface and require frequent handovers, GEO satellites provide a stable and uninterrupted communication link. Their high vantage point and wide field of view make them invaluable for monitoring both terrestrial and space weather phenomena.

Equipped with sophisticated onboard instruments such as the Geostationary Lightning Mapper (GLM), Advanced Baseline Imager (ABI), Solar Ultraviolet Imager (SUVI), and magnetometers, GEO satellites

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collect critical data on lightning activity, atmospheric conditions, solar irradiance, and geomagnetic fields. This information supports a wide array of scientific and operational objectives—from early storm detection and wildfire tracking to monitoring space weather events that could disrupt satellite communication and terrestrial power systems.

By offering continuous observation from a fixed orbital position, GEO satellites play a vital role in enhancing global forecasting capabilities, improving climate research, and ensuring reliable communication infrastructure around the world.

2. LITERATURE SURVEY

Emran, et al [1] provided a holistic understanding of current advancements, highlighting both achievements and areas requiring further exploration, and sets the stage for the development of robust, scalable, and ethical fraud detection frameworks.

Zhan, et al [2] explored the limitations of RPA, such as its challenges in processing unstructured data and handling complex decision-making scenarios. Looking forward, it considers the future trends in AI and RPA, emphasizing the benefits of cloud technology in scaling automated systems and addressing associated challenges.

Manoharan, et al [3] proposed an article by using ultrasonic transducer and an Internet-connected computer, like a Raspberry Pi, to keep track of inventory the current stock levels on a webpage that our system hosts and sends an email to the supplier and/or corporate staff to place an order.

Xu, et al [4] proposed a personalized recommendation system leveraging the BERT model and nearest neighbour algorithm, specifically tailored to address the exigencies of the eBay e-commerce platform. The efficacy of this recommendation system is substantiated through manual evaluation, and a practical application operational guide.

Albahri, A, et al [5] identified several unused and used areas in natural disaster- based AI theory, collects the disaster datasets, ML, and DL techniques, and offers a valuable XAI approach to unravel the complex relationships and dynamics involved and the utilization of data fusion techniques in decision-making processes related to natural disasters. Finally, the study extensively analysed ethical considerations, bias, and consequences in natural disaster- based AI.

Bello, H.O.; et al [6] provided a resilient defence against evolving fraud schemes, enhancing the security and integrity of financial transactions. This adaptive approach not only mitigates financial risks but also strengthens the overall trustworthiness of financial systems.

Weegar, R.; et al [7] produced a subset of answers to the exam questions was manually graded and next used as training data for machine learning models classifying the remaining answers. A number of different strategies for how to select which answers to include in the training data were evaluated. Compared to fully manual grading, the overall reduction of workload was substantial—between 64% and 74%—even with a complete manual review of all classifier output to ensure a fair grading.

Li, K.C.; et al [8] provided the supplementary information about students, such as past course grades and factors contributing to the predicted risk levels, for instructors' reference to inform learning support strategies. Preliminary evaluation results show that the platform correctly identified about 39% of students who failed their courses. The results suggest that some students who were predicted as having a high risk of failing at the beginning of a course would eventually pass with the learning support provided after early identification. This demonstrates the effectiveness of the platform in enhancing student success through proactive support enabled by early prediction of academic risk.

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Edwards, M.R.; et al [9] investigated how to make effective business decision with this updated edition that includes the latest materials on predicting attrition with machine learning, biased algorithms and data protection, supported by online resources consisting of R and Excel data sets.

Lee, J.; et al [10] developed a conceptual model of positive employee experience using sentiment analysis within algorithm-based human resource (HR) strategies. Its goal is to enhance HR professionals' understanding of employee experiences and enable data- driven decision-making to create a positive work environment, thereby contributing to the originality of HR research.

Wu, X, et al [11] focused on improving model interpretability, optimizing large- scale data processing capabilities, expanding cross-domain applications, and strengthening data security and privacy protection to promote the widespread application and development of adaptive machine learning technology.

Chaudhary, G., et al [12] examined regulation of algorithmic transparency in the EU, specifically provisions under the General Data Protection Regulation (GDPR), it aims to situate analysis of the GDPR's provisions on explainability of AI systems within broader technology ethics and policy discourse. The paper's scope is limited to EU regulations applicable to AI data processing transparency.

Srivastava, K., et al [13] three case studies has been conducted, and the results are compared. Challenges such as scalability issues and ethical considerations, including biases and fairness, are discussed. Looking ahead, we offer insights into future XAI research trajectories, aiming to foster public trust and shape a future where AI systems are both intelligent and comprehensible.

3. PROPOSED METHODOLOGY

A Dense Probability Feature Neural Network (DPNN) is a deep learning model that integrates dense layers with probabilistic feature representations to improve classification and prediction accuracy. It extracts features by mapping input data into probabilistic feature spaces capturing uncertainities and variations.

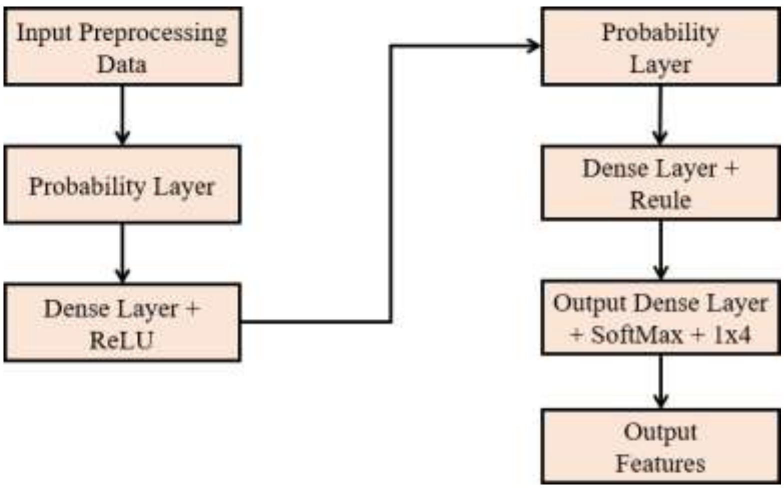

Fig. 1: Block Diagram of DPNN.

A decision tree classifier operates as a supervised learning algorithm used for classification tasks by breaking down data into smaller subsets based on feature conditions. The process starts with a root node, which represents the entire dataset. The algorithm selects the best feature to split the data based on specific criteria, such as Gini impurity or entropy. These criteria measure the homogeneity of data within a node, aiming to create subsets that are as pure as possible.

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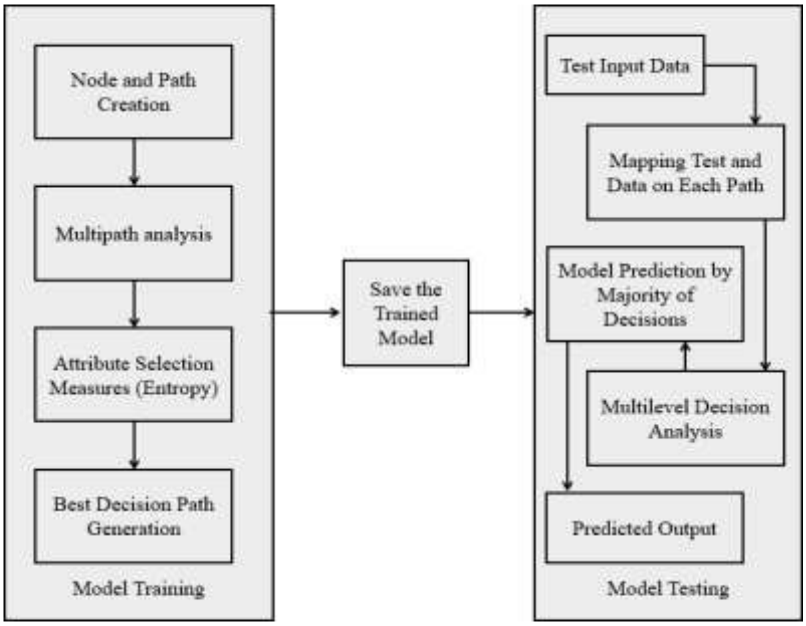

Fig: 2: Decision Tree Classifier

4. RESULTS AND DISCUSSION

Figure 3 showcases the process of uploading the dataset into the system. The dataset consists of 163,741 rows and 22 columns, containing various network parameters, geographical coordinates, signal quality metrics, and mobility information. The uploaded dataset enables further analysis and preprocessing for machine learning-based classification and prediction tasks.

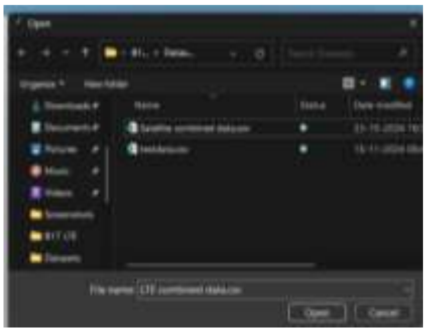

Fig. 3: Dataset Uploading

Figure 4 shows a count plot representing the frequency distribution of the 'path' variable, which categorizes the mobility patterns. The bar chart effectively visualizes the count of each class, such as 'car', 'train', 'pedestrian', and 'static', providing insights into the dataset's class distribution. This visualization is essential for understanding data balance and aids in identifying any class imbalances that might affect model training and performance.

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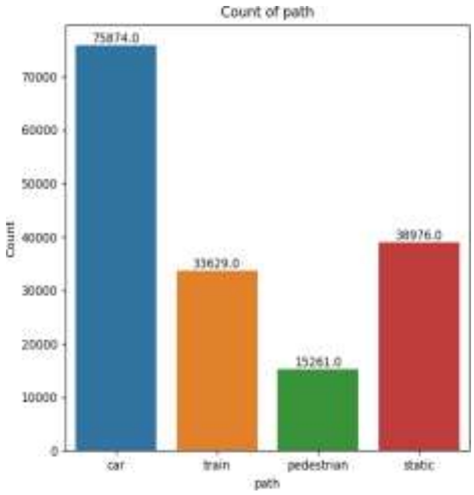

Fig. 4: Count of Path

Figure 5 provides a confusion matrix for the DPNN with DTC model, illustrating that nearly all test samples are correctly classified into their respective categories.

Fig. 5: DPNN with DTC model Confusion Matrix

Figure 6. is divided into two sections. The first section displays a preview of the newly uploaded test dataset, which includes 20 rows and 21 columns. The dataset features columns such as "Unnamed: 0," "Timestamp," "Longitude," "Latitude," and several network metrics like "ServingCell_Lon," "ServingCell_Lat," and "ServingCell_Distance." Sample values indicate that the dataset contains diverse geographical and temporal data points—for instance, the first few rows show consistent measurements recorded on "2017.12.04" with longitude values around -8.499297 and latitude values near 51.901570, while later rows, such as those with indices 109499 to 109502, show data recorded on "2018.02.11" with slightly different coordinates and distances.

The second section presents the same dataset after the prediction process, where an additional column, "Predicted," has been appended. This column contains the mobility category predicted by the model for each row. For example, rows 0 to 5 are predicted as "car," whereas rows 6 to 19 are classified as "static." The predictions indicate that the model distinguishes between different mobility patterns based on the provided features, demonstrating its capability to generalize to unseen data.

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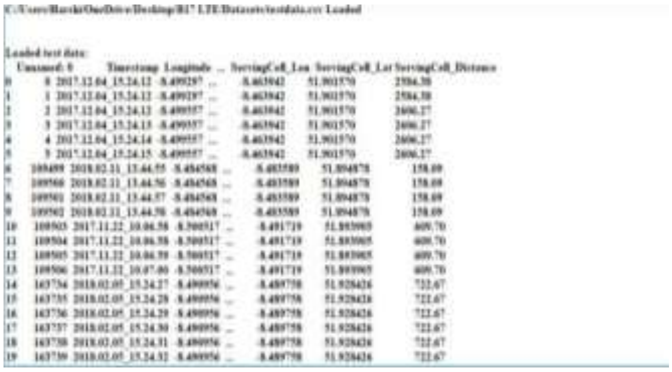

Fig. 6: Prediction test data Uploaded

Table 1 showcases the performance of the Deep Probabilistic Neural Network (DPNN) with Decision Tree Classifier (DTC), which achieves near-perfect accuracy of 99.997%, with equally impressive precision, recall, and F1-score values, all hovering around 99.997%. This signifies that the model makes almost no errors in its predictions.

Table 1: DPNN with DTC Model Performance

Metric	**Value (%)**
Accuracy	99.997
Precision	99.996
Recall	99.998
F1-Score	99.997

5. CONCLUSION

The proposed machine learning approach significantly enhances the accuracy of mobility pattern predictions, leading to more reliable satellite communication by reducing uncertainties in movement forecasting. By effectively identifying these mobility patterns, the system optimizes resource allocation, ensuring better distribution of communication resources, minimizing signal transmission errors, and improving overall coverage. Unlike traditional static models, the adaptive learning techniques employed dynamically adjust to changing mobility conditions, thereby enhancing network efficiency and responsiveness. Additionally, the classification-based methodology refines trajectory adjustments, reducing network downtime and ensuring uninterrupted satellite services. Furthermore, this approach offers scalability and versatility, making it applicable to various satellite orbits and communication scenarios, ultimately providing a flexible and robust solution for dynamic space environments.

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