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RESEARCH ARTICLE

Quad-Tree-Based Driver Classification Using Deep Learning for Mild Cognitive Impairment Detection

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ABSTRACT Given GPS points on a transportation network, the goal of the Quad-tree Based Driver Classification (QBDC) problem is to identify whether drivers have Mild Cognitive Impairment (MCI). The QBDC problem is challenging due to the large volume and complexity of the data. This paper proposes a quad-tree based approach to the QBDC problem by analyzing driving patterns using a real-world dataset. We propose a geo-regional quad-tree structure to capture the spatial hierarchy of driving trajectories and introduce new driving features representation for input into a convolutional neural network (CNN) for driver classification. The experimental results demonstrate the effectiveness of the proposed algorithm, achieving an F1 score of 95% that significantly outperforms the baseline models. These results highlight the potential of geo-regional quad-tree structures to extract interpretable features and describe complex driving patterns. This approach offers significant implications for driver classification, with the potential to improve road safety and cognitive health monitoring.

INDEX TERMS Spatiotemporal data, GPS data, trajectory analysis, driving behavior, older driver classification, quad-tree decomposition, convolutional neural networks.

I. INTRODUCTION

Given GPS points on a transportation network, Quad-tree Based Driver Classification (QBDC) aims to identify whether drivers have Mild Cognitive Impairment (MCI). The QBDC plays a key role in improving road safety and reducing the risks associated with cognitive decline. MCI can result in incorrect turns, missing intended routes or exits, going wrong ways, and increasing the risk of accidents. This problem is challenging because of the extensive trajectory data and different spatial-temporal driving behaviors of populations. Raw GPS trajectories contain only a sequence of GPS points without meaningful correlations and explicit features for feeding into a supervised model. To remedy this issue, we propose a quad-tree based structure to obtain meaningful features while preserving the timestamped sequence of data points. This approach enables us to identify driving patterns and the shape of the trips. Figure 1 shows an example input of the problem with GPS points within a trip. Every point has a time stamp, longitude, latitude and direction. Here, each set of points belongs to a driver's trip with different source and destination locations.

This study presents an innovative geo-regional quad-tree approach for driver classification using GPS trajectory data. Our method decomposes GPS trajectories into hierarchical spatial regions, enabling a multiresolution representation of sub-regions [13] within each trip. By applying binary encoding to quad-tree nodes, we generate location-based

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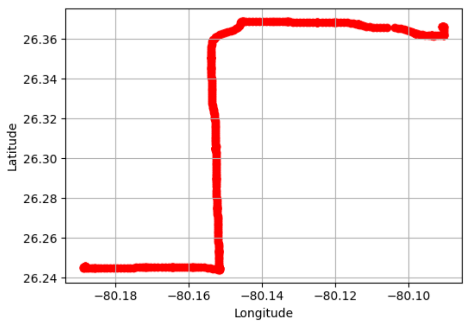


FIGURE 1. Time series GPS points partitioned within a trip.

features from trip data. These features are then processed through a 2-dimensional Convolutional Neural Network (2D CNN) to effectively classify drivers. The hierarchical structure of the quad-tree organizes GPS data into nested regions, allowing for a clear and detailed representation of driving paths. This structure captures spatial details and variations in driving behavior, which are essential for identifying the shape of a trip. Extensive experimental validation with real-world telematic data demonstrates the efficacy of this approach in accurately distinguishing between drivers with and without MCI. By combining location-based features with deep learning, our framework provides a scalable and practical solution for early cognitive health monitoring, enhancing road safety and promoting proactive public health measures.

A. APPLICATION DOMAIN

In recent years, researchers have identified MCI through cognitive assessments and an individual's medical history.[1] MCI can affect daily activities such as driving behavior and raise the likelihood of progressing to dementia, particularly Alzheimer's disease [27]. Alzheimer's disease is a severe condition that progressively damages brain cells and has substantial financial and social challenges [21], [22]. Detecting MCI, an early indicator of Alzheimer's is essential for implementing timely interventions to slow or prevent further cognitive deterioration [23]. MCI can be related to driving performance because it impacts the cognitive abilities necessary for safe driving 1. Individuals with MCI can hinder their ability to make quick and accurate decisions while driving. For instance, memory issues may cause difficulties in following directions, resulting in missed turns. Inattention can affect a driver's capacity to observe other vehicles and pedestrians, while slower reaction times can delay responses to sudden changes on the road and increase accident risks [27]. Identifying older drivers with MCI is important for improving public health and road safety. Early detection of MCI in older citizens can help ensure the safety of these drivers and others on the road. Furthermore, the classification of drivers with MCI can aid insurance companies in better assessing risks and creating incentive programs that encourage safer driving habits. GDBC problem enables technological advancements by integrating telematics and machine learning within the healthcare and safety sectors. In-vehicle sensing technology represents an innovative approach to assessing driver behavior and monitoring cognitive decline. This technology has evolved significantly and provides effective and affordable solutions for diagnosing early-stage dementia in older drivers based on their driving patterns [27], [28], [29], [30], [31].

[1] https://www.fau.edu/newsdesk/articles/older-drivers-research.php

B. PROBLEM DEFINITION

In formulating the QBDC problem, a spatiotemporal network is represented and analyzed through the diverse trips taken by multiple drivers. The problem is defined as follows:

Input:
- A set of trajectory data containing latitude, longitude, direction, distance between consecutive points and timestamps,
- A set of drivers ID,
- A set of Trip Numbers T,
- A set of Labels $L = \{\text{MCI}, \text{non-MCI}\}$,
- The minimum length of a trip α

Output:
- Classifying drivers based on their trips with varying origin-destination locations.

Objective:
- Maximize the predictive performance to classify driving patterns.

Constraints:
- The length of a trip $> \alpha$.

C. OUR CONTRIBUTION

In this paper, we introduce a novel approach to QBDC based on the idea of region quad-tree [3]. Our contributions are as follows:

1) We introduce the QBDC problem, classifying older drivers into MCI and non-MCI categories using GPS data.
2) We propose the geo-regional quad-tree approach to generate new location-based features and effectively classify the driving patterns of older citizens.
3) We conduct extensive experimental evaluations of the proposed algorithm using real-world telematic data.

D. RELATED WORK

Extensive research has been conducted on using movement features to examine trajectory data and analyze driver behavior. For instance, Dodge et al. used direction, speed, and acceleration to identify trajectory similarity and detect anomalous driving styles [1]. With the advantages of machine learning, more sophisticated models have been developed to improve classification and detection [2], [4], [6].

Wang et al. employed Support Vector Machines (SVM) to classify drivers based on their GPS trajectories and

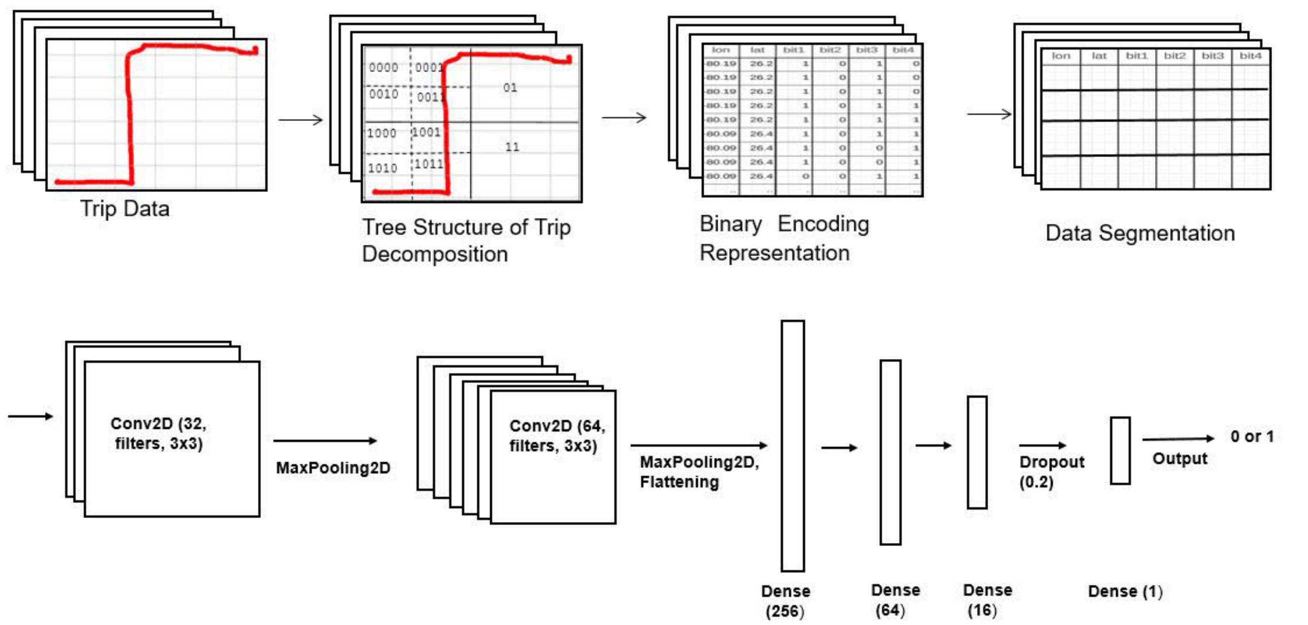


FIGURE 2. The proposed model.

demonstrate the potential of these methods in handling large datasets [5]. Yu et al. proposed a deep learning framework and used a variational autoencoder to identify the level of abnormality for a set of drivers. Their proposed approach divides the trajectory data to generate spatiotemporal units with homogenous properties. Then, aggregate the parameters of acceleration, speed, and direction within each spatio-temporal unit, which aggregation may cause some information loss [12]. Zhang et al. employed CNN to capture spatial dependencies in GPS trajectories, effectively distinguishing between different driving patterns [9]. In recent work, Li et al. introduced a Transformer-based encoder-decoder network combined with contrastive learning to represent trajectory data without requiring summarization [14]. They incorporated the Hilbert curve within a multi-scale spatial-aware embedding module, which was subsequently fed into the Transformer-based sequence modeling module for further processing. This method maps each geographical coordinate (latitude, longitude) to a one-dimensional index along the Hilbert curve [14].

Additionally, Huang used a higher-order Markov chain to detect anomalous driving behaviors, such as long-distance detours and high-density sequences of turns. The approach employs a recursive Bayesian filter that dynamically infers the probability of these anomalies over time. The algorithm incorporates a threshold for heading changes to filter out trivial movements, enabling the identification of cyclic patterns and loops [10]. Zhang et al. detect detour behavior in trajectory data by focusing on trajectories with the same starting and ending points. The similarity between these trajectories is measured using Dynamic Time Warping (DTW), which accounts for temporal misalignments between trajectories. DTW calculates the Euclidean distance between corresponding points on the trajectories to determine their similarity. The calculated similarities are then input to the Isolation Forest (iForest) algorithm, which identifies anomalous trajectories [15]. Jiang et al. defined detours as unnecessary deviations in a route that results in increased travel time or distance between consecutive query locations. These detours typically occur when a route includes unintended stops that are not aligned with the specified query locations. The authors use a variance-based approach that analyzes travel time distributions between locations to address this. Trajectories with travel times outside the normal range are flagged as detours and excluded, ensuring the final recommended route is both direct and efficient [17].

Integrating knowledge graphs with trajectory data has opened new avenues for context-aware analysis and outlier detection. Ahmed et al. propose a method for constructing normal and outlier graphs from trajectory data, representing these as directed weighted graphs. The normal graphs capture typical trajectories, while outlier graphs are based on significant deviations. The method involves comparing input trajectories with these target graphs through similarity analysis of nodes and edges, which correspond to visited points and paths. The comparison employs containment similarity and maximum common subgraph similarity, allowing for the effective classification of trajectories as either normal or outliers [11]. With the advent of increasingly available GPS trajectory data and Convolutional Neural Networks, researchers proposed a Deep Convolutional Neural Network for Vehicle Classification (CNN-VC) to identify the types of vehicles from their trajectory [16]. Huang et al. used a quad-tree based method to simplify GPS trajectories by integrating geographic context and adjusting the level of detail across trajectory segments. The approach focuses on preserving finer details in critical areas like road intersections and landmarks [19]. Data is aggregated within each quad-tree node to reduce the number of points, which may result in some information loss. Park proposed a hierarchical binary quad-tree index for efficiently managing and querying spatial data [18]. The quad-tree is used to represent the locations of objects in a hierarchical grid structure. The grid is recursively divided until each cell contains only one object, ensuring that every single object has its unique representation within the grid [18].

In the realm of disease detection, numerous approaches have been developed, ranging from medical tests [20] to gait tests [23], [24], balance test scores [25], and reinforcement learning for predicting response to medications [26]. However, our research takes a novel quad-tree based approach by leveraging trajectory data, specifically driving behaviors, to detect MCI.

E. SCOPE AND OUTLINE

The rest of the paper is organized as follows: Section II describes our proposed approaches to QBDC. We provide the experimental setups and corresponding results in Section IV followed by a detailed discussion in Section V. Finally, Section VI concludes the paper.

II. PROPOSED METHODOLOGY FOR QBDC

In this section, we introduce the benefit of the region quad-tree approach [3] in extracting useful location-based features from trajectory data and accommodating trips with varying shapes, start points, and endpoints. Summarizing data can cause inaccurate estimation due to the difficulty of limiting the loss of information [12]. Unlike existing methods [12], [13], [14], [15], [16], [17], [18], [19] that rely on aggregated features, we introduce a quad-tree based approach that utilizes all GPS points of a trip.

Figure 2 depicts the pipeline of our proposed geo-regional quad-tree approach for QBDC problem. The process begins with raw GPS trip data, which includes timestamps, latitudes, longitude, and direction. The geo-regional quad-tree approach decomposes the trip into subregions while preserving the timestamped sequence and topological connectivity of the GPS points. Each subregion is then represented in meaningful binary format, with unique binary codes assigned to each. Using a geo-regional quad-tree enables us to identify the hierarchical structure of the trips with various driving patterns, such as cyclic patterns and road repetitions. In this simple example, the binary codes are represented as bit1 through bit4. These binary-encoded features are subsequently input into a 2D CNN for further processing and classification.

A. BASIC CONCEPT

The shape of driving patterns depends on changes in the path and the sequence of visited regions, which can provide insights into how the journey unfolds over time and space. Analyzing the shape of the trips can reveal valuable information about driver behavior. Figure 3 shows potentially abnormal driving styles such as repeated path selections, cyclic patterns, and long-distance U-turns [29]. These kinds of driving behavior may suggest difficulty navigating new areas, confusion or a need to revisit places and going the wrong way. To uncover abnormal driving behavior, it is essential to analyze directional deviation changes and measure the lengths of these deviations. By decomposing the trip into meaningful regions, we can further examine direction changes and distances covered. This decomposition helps focus on specific parts of the journey, making it easier to analyze how direction changes occur within each region and how far the driver travels in those segments.

B. QUAD-TREE STRUCTURE AND OPERATIONS

1) GEO-REGIONAL QUAD-TREE STRUCTURE FOR TRIP DECOMPOSITION

Region quad-tree recursively divides a 2-dimensional space into four quadrants of the same size [3] (Figure 4). Quad-tree structures have many applications in image processing and spatial indexing [13]. We extend the region quad-tree concept [3] by introducing the geo-regional quad-tree to identify various trip shapes.

The decomposition process starts with a root node representing the whole trip. When the attributes of points within the root node do not meet a specified threshold, the geo-regional quad-tree subdivides the root into four child nodes. Each node also follows a threshold; if it does not satisfy the criteria, the process further subdivides it into four smaller regions and creates new child nodes (Figure 4). This recursive decomposition continues until all regions meet the predefined criteria.

Leaf nodes at the edges of the quad-tree's spatial boundaries do not have children and represent the smallest regions in the quad-tree. They store the data points, ensuring each region contains a manageable feature of points and has a parent node (Figure 4).

Let R represent the root node of the quad-tree, which corresponds to the entire spatial region of a trip. The region R is defined by its minimum and maximum latitude $(\mathrm{lat}_{\min}, \mathrm{lat}_{\max})$ and longitude $(\mathrm{lon}_{\min}, \mathrm{lon}_{\max})$ values. The minimum and maximum latitude and longitude values of all the points within a region determine the boundary of a node in the quad-tree and define the spatial region it covers. The quad-tree recursively partitions R into four quadrants (child nodes) until a stopping criterion is met. Each quadrant Q_i (where $i \in \{1, 2, 3, 4\}$) is defined by its spatial boundaries:

$$Q_i = \left[\mathrm{lat}^i_{\min}, \mathrm{lat}^i_{\max}\right] \times \left[\mathrm{lon}^i_{\min}, \mathrm{lon}^i_{\max}\right]$$

where $\mathrm{lat}^i_{\min}, \mathrm{lat}^i_{\max}, \mathrm{lon}^i_{\min}, \mathrm{lon}^i_{\max}$ are the latitude and longitude boundaries of the i-th quadrant. To construct a quadtree, each of the n points is inserted individually by traversing the hierarchical structure to locate its appropriate quadrant. Since the depth of a balanced quadtree is at most $O(\log n)$, each insertion takes $O(\log n)$ time. Consequently,

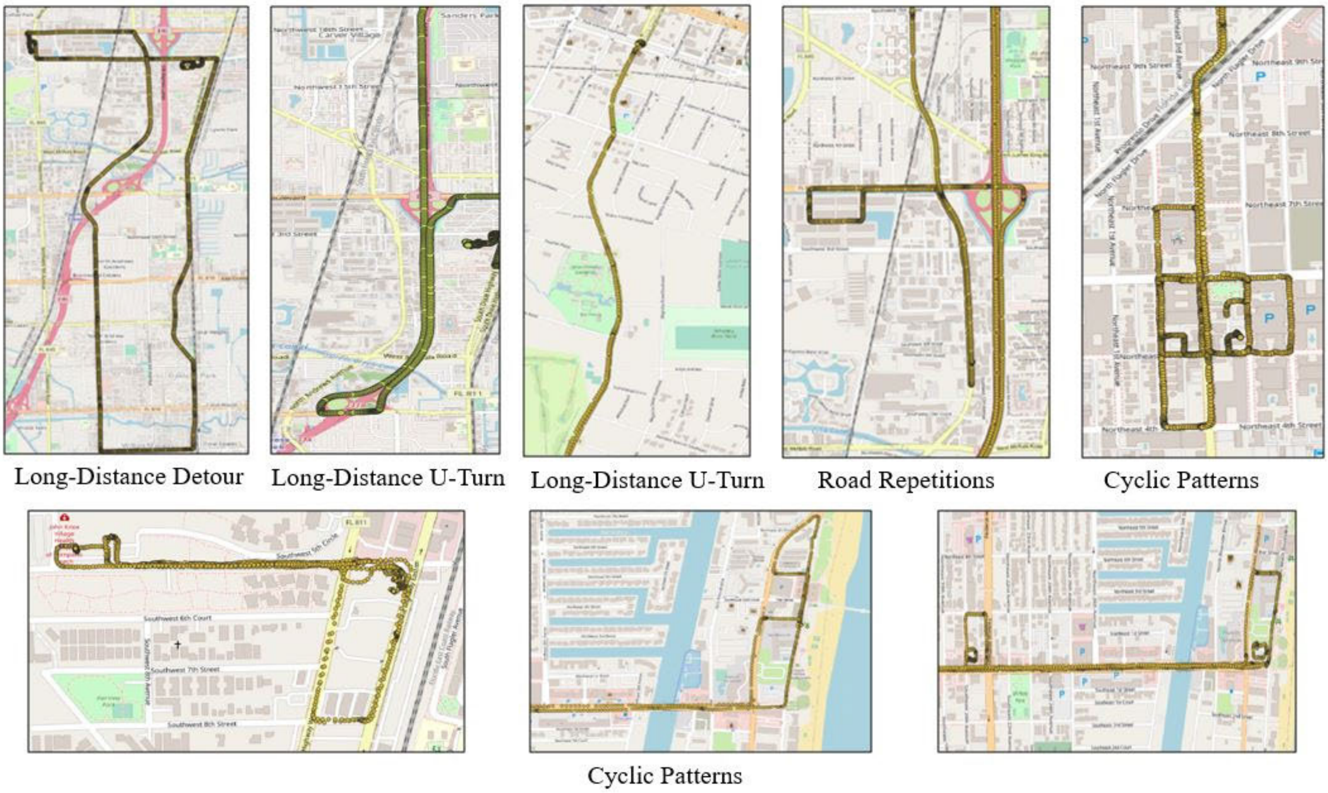


FIGURE 3. Visual representation snapshot of potentially abnormal trips from the real-world dataset utilized in this study [29].

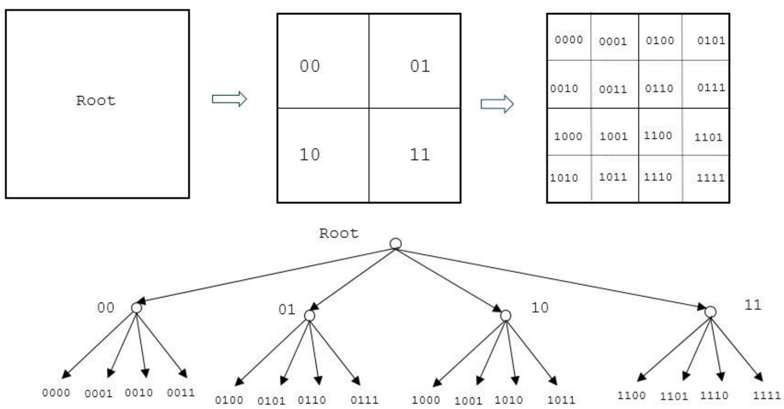


FIGURE 4. Spatial decomposition and hierarchical structure of a quad-tree with binary encoding.

the total time complexity for constructing the quadtree is $O(n \log n)$.

2) BINARY ENCODING OF QUAD-TREE NODES

After decomposing a trip using the geo-regional quad-tree, the sub-regions have unique representations based on their topological connectivity and the information of their GPS points. Figure 4 illustrates the quad-tree's hierarchical structure and spatial decomposition process for dividing a two-dimensional grid into smaller regions for spatial indexing. Each node in the quad-tree represents a distinct region and receives a unique binary code based on its position. Beginning with the root node, the four child nodes can be encoded as follows:

- Top-left = 00
- Top-right = 01
- Bottom-left = 10
- Bottom-right = 11

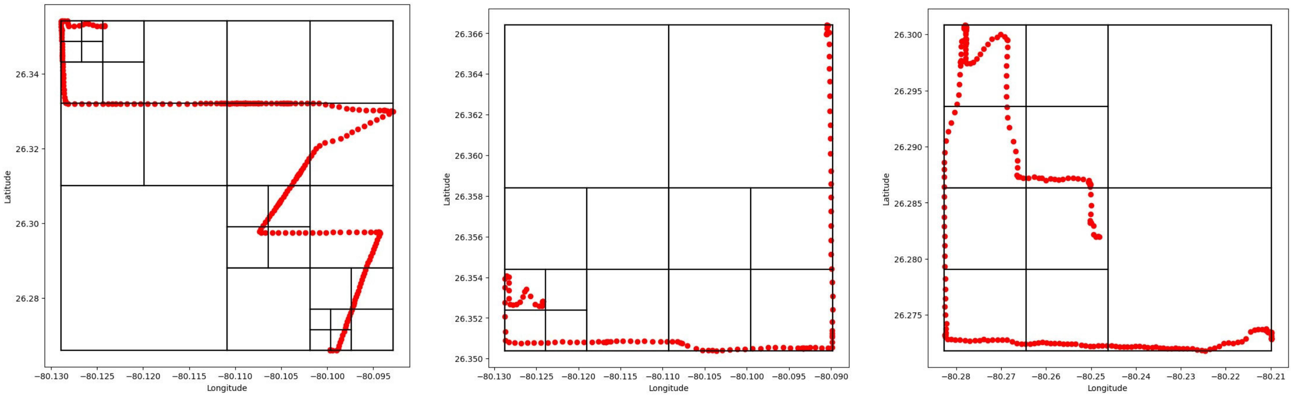


FIGURE 5. **Real-world examples of the built quad-tree with the same splitting threshold.**

3) THRESHOLDS CRITERIA

The essential parameter of the geo-regional quad-tree decomposition is stopping criteria. The threshold criteria can be defined as follows:

- Direction consistency: We represent the direction of GPS points using rounded values of 0°, 90°, 180°, and 270° to manage data complexity while preserving essential directional information. To obtain these values, we calculated the azimuth (or bearing) between consecutive GPS points, providing the angle from true north to the line connecting each point. Each azimuth was then rounded to the nearest cardinal direction. Trip shape analysis involves examining these directions to identify patterns. In a geo-regional quadtree, each node has a value representing the direction of the GPS points within its region. If all points within a node share the same rounded direction, the node will not subdivide. This approach is simplifying the structure and ensuring efficient data handling without loss of critical spatial information.
- Sum of distances: Besides the direction consistency, we check if the sum of the distances between the GPS points in a node is less than a threshold; the node will not be subdivided. This criterion enables us to skip unnecessary information while maintaining acceptable resolution in more detailed, heterogeneous areas. We used the Haversine formula to calculate the shortest distance between two points on the surface of a sphere.
- Maximum points per Node: To avoid excessive subdivisions, we applied an additional criterion based on the density of GPS points, ensuring that each node holds more than a predefined number of points.

Figure 5 illustrates examples of the constructed quad-tree with the same splitting threshold, demonstrating how the decomposition process subdivides the space into smaller regions based on predefined stopping criteria. A larger threshold results in fewer subdivisions and larger boundary leaf nodes in the quad-tree decomposition. Figure 6 and 7 depict examples of this effect. Figure 6 shows the quad-tree partitioning of vehicle trajectories with a 50-meter sum of distance threshold between every consecutive GPS point, leading to more detailed divisions. Figure 7 demonstrates the same process with a 500-meter threshold, resulting in a larger resolution. Both figures use a maximum of 10 points per node to regulate the partitioning.

4) TREE STRUCTURE OF TRIP DECOMPOSITION

The binary code helps identify the region of each point within the overall trip. Figure 8 shows how the geo-regional quad-tree works by giving each point in a trip a region binary code. The quad-tree recursively divides the space into quadrants, with each region receiving a unique binary identifier. This approach facilitates critical spatial operations such as finding adjacent region sequences and resolution representation.

- Adjacent Region Sequences: By analyzing the sequence of node names in adjacent regions, it is possible to detect whether a driver revisits the same area over time. In the geo-regional quad-tree structure, nodes that share the same parent are considered part of the same region and are adjacent. Sibling nodes with a common parent represent nearby geographic areas. Figure 9 illustrates how cyclic patterns in a vehicle's trajectory can be identified using the geo-regional quad-tree. A cyclic pattern emerges when the vehicle revisits the same regions during its trip. This occurs when GPS points pass through a series of regions (nodes) and eventually return to a previously visited larger region or its parent node.
- Resolution representation: The density of GPS points within a region can reveal directional deviations and potential cyclic driving patterns in specific areas. Figure 9 demonstrates how effectively the quad-tree decomposition captures driving patterns on both local roads and highways. It highlights the diversity in predefined region sizes, enabling variable-resolution representation of geographic areas. The hierarchical structure of the quad-tree helps to subdivide regions with high GPS point density into smaller boundary nodes, typically corresponding to local roads. In contrast, regions with a lower density of points are divided into larger areas, likely representing highways.

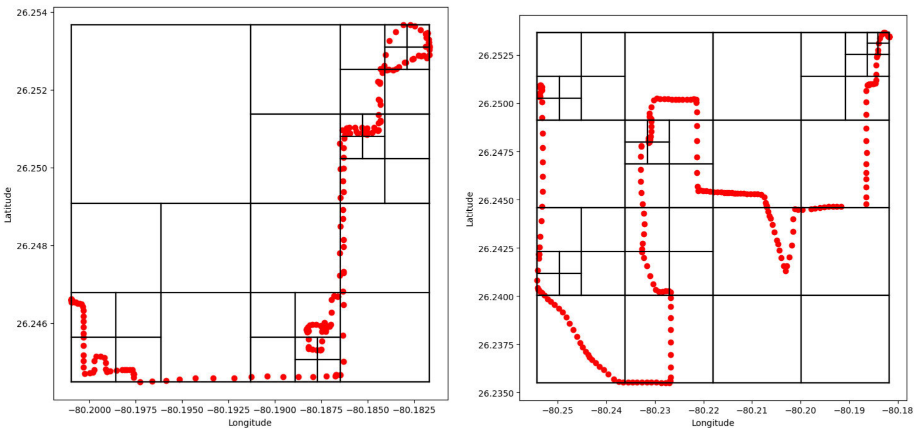


FIGURE 6. **Quad-tree partitioning GPS point in a real-world trip with the 50-meter sum of distance threshold.**

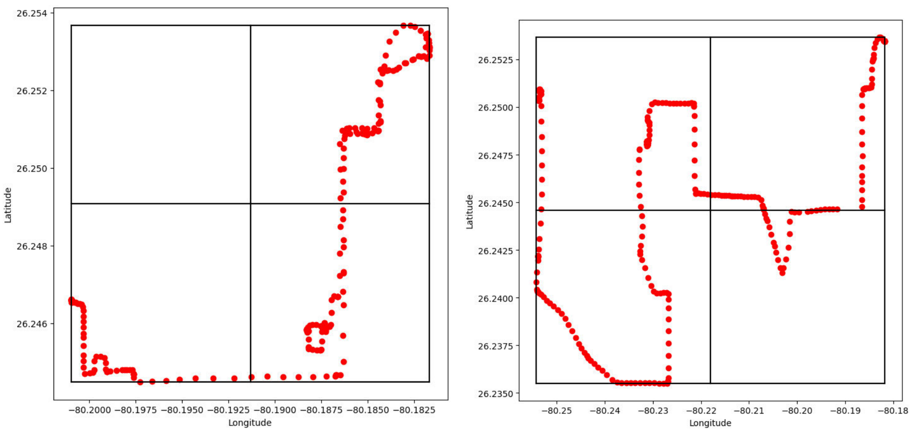


FIGURE 7. **Quad-tree partitioning GPS point in a real-world trip with a 500-meter sum of distance threshold.**

By encoding trajectory data in binary format, we can leverage data-driven techniques like deep learning to efficiently process and analyze the hierarchical data.

5) DATA SEGMENTATION

We employ a non-overlapping sliding window technique to address the challenge of variable-length sequences in trajectory data 2. This method involves breaking down the trajectory data into smaller, fixed-length segments consistent in size, essential for 2D CNN processing.

C. LEARNING WITH 2D CONVOLUTIONAL NEURAL NETWORK

A 2D CNN is a deep learning model designed for analyzing structured data, such as images and time series data [32]. It uses convolutional layers to detect features and patterns within the data, pooling layers to reduce dimensionality while retaining important information, and fully connected layers for final predictions [32]. While commonly used for image recognition, 2D CNNs can be applied to time series data by transforming it into 2D representations, enabling applications like speech recognition and audio classification [32]. Based on our knowledge, there have been few efforts to apply deep learning, specifically 2D CNNs, to trajectory data analysis.

Our model (Figure 2) consists of two convolutional layers with 32 and 64 filters, using 3×3 kernels and ReLU activation. Each convolutional layer is followed by a 2×2 max-pooling layer with a stride of 2, which reduces spatial dimensions while preserving essential features. The output is then flattened and passed through three fully connected layers with 256, 64, and 16 units, all activated by ReLU. To improve training stability, batch normalization is applied after the convolutional layers and the second fully connected layer. A dropout layer is placed before the final output to prevent overfitting and promote better model generalization. The final fully connected layer outputs two classes: MCI and non-MCI. The model uses the Adam optimizer with a learning rate of 0.001 and is trained with a batch size of 64 for 100 epochs. Early stopping is used to prevent overfitting by halting training if the validation performance does not improve for a specified number of epochs. Table 1 provides an overview of the 2D CNN architecture.

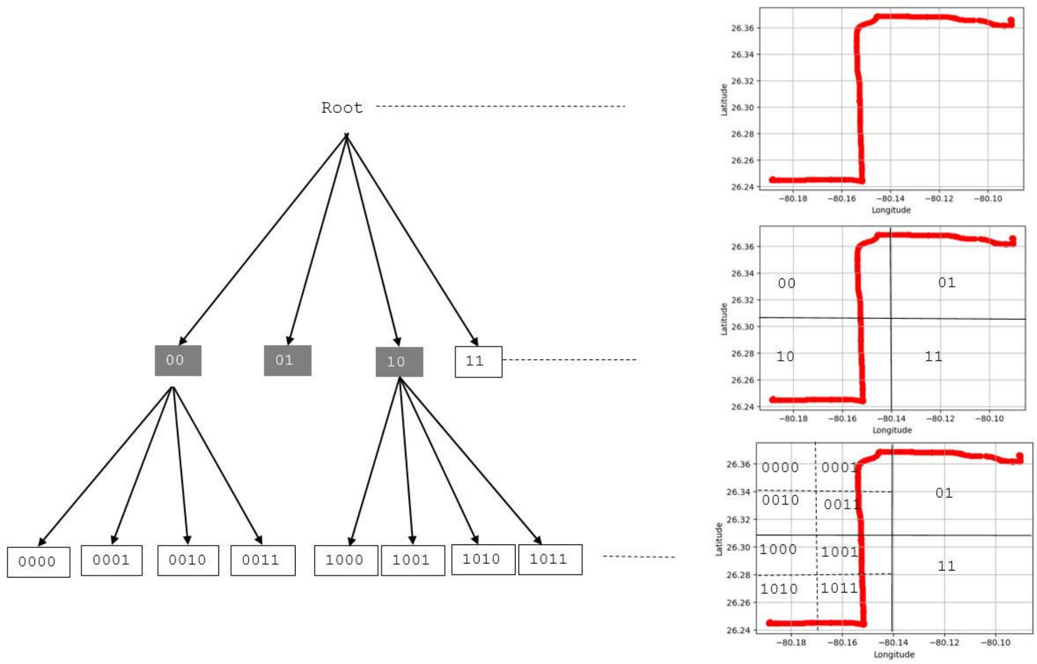


FIGURE 8. Tree structure of trip decomposition and binary encoding of quad-tree nodes.

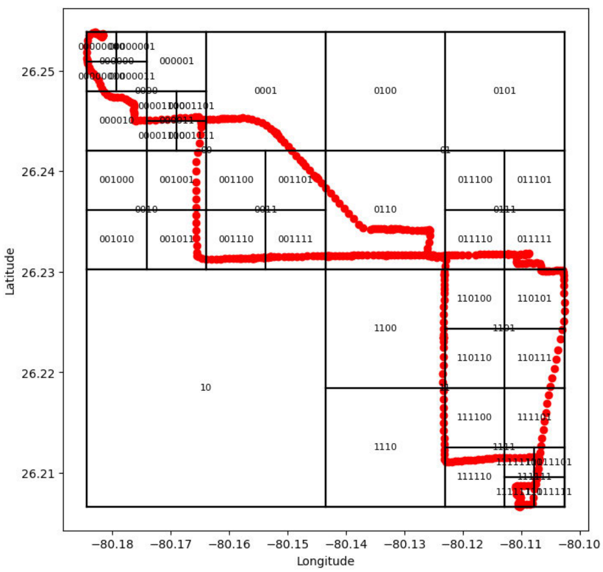


FIGURE 9. Cyclic pattern in real-world vehicle trajectory data showing GPS points revisiting adjacent regions with common parent nodes.

III. DATA COLLECTION

The dataset we utilized in this research was sourced from an extensive five-year study conducted at Florida Atlantic University and the University of Central Florida. This study utilizes real-world trajectory datasets from a five-year NIH-funded project involving 236 older drivers aged 65 to 91 years, providing a robust and diverse dataset for analyzing driving behaviors. Over four years, we collected

TABLE 1. 2D CNN architecture overview.

Layer Type	Filters/Units	Kernel/Pool Size	Activation
Conv. Layer 1	32	3x3	ReLU
Batch Norm 1	-	-	-
Max-Pooling 1	-	2x2	-
Conv. Layer 2	64	3x3	ReLU
Batch Norm 2	-	-	-
Max-Pooling 2	-	2x2	-
Flatten	-	-	-
Dense Layer 1	256	-	ReLU
Dense Layer 2	64	-	ReLU
Batch Norm 3	-	-	-
Dense Layer 3	16	-	ReLU
Dropout	-	-	-

and stored more than 72000000 real-time trajectories, pre-processing them to eliminate errors and noise while ensuring data accuracy by comparing RPM, speed, direction, and engine load. The nursing College initially evaluated older drivers using the Montreal Cognitive Assessment (MoCA) to determine eligibility for the study, with participants scoring 19 or higher included to ensure a baseline level of cognitive function [28]. To ensure accurate ground truth labels for MCI, we performed detection using clinical evaluations, psychometric tests, and behavioral data analysis [28]. Clinical Dementia Rating (CDR) scores and neuropsychological tests evaluate cognitive function. We tracked cognitive changes through assessments performed every 3 months for 4 years,

FIGURE 10. Overview of the Raspberry-based TMU [27].

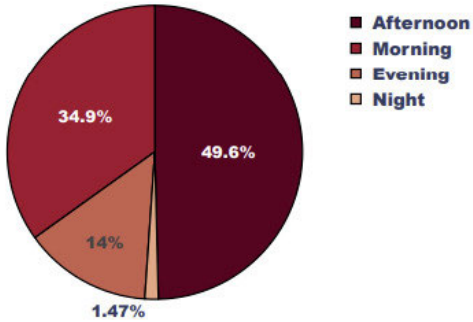


FIGURE 11. Distribution of trips across different times of the day [27].

using a double baseline design to minimize practice effects. Statistical adjustments, such as Reliable Change Indices (RCIs), are applied to ensure the accuracy of detecting true cognitive decline [28].

The in-vehicle sensing system, which includes telematic was installed on participants' vehicles to collect driving behavior datasets over four years.

Telematics Monitoring Units (TMUs) are built on the Raspberry Pi 4 Model B and developed by AutoPi (Figure 10). TMU includes a GPS sensor, an Inertial Measurement Unit (IMU), an onboard diagnostics (OBD) connector, a 4G/LTE cellular modem, an SD card, and a USB flash drive. The IMU records the vehicle's movements and orientations, providing data on acceleration, braking, and angular motion. The GPS sensor tracks the vehicle's location, including timestamp, latitude, longitude, and altitude, helping to analyze travel distance. The Course Over Ground (COG) data from the GPS helps determine the vehicle's direction. The OBD connector provides engine RPM, Speed over Ground(SOG), and fuel system status.

This dataset encompasses additional driving behavior and statistical features obtained from in-vehicle sensing systems. The features are trip duration, distance, acceleration, speed, engine load, and temperature metrics. To gain more insights into driving behavior, we also analyzed the time of day for a subset of participants, categorizing trips into four periods [27]. Figure 11 shows the distribution of trips across morning, afternoon, evening, and night. Results indicate that 50% of trips occur in the afternoon and 34.9% in the morning, suggesting a preference for driving during daylight hours [27]. The utilized dataset is comprehensively detailed in our previous publications [27], [28], [29], [30], [31].

In our work here, each trip is divided into fixed-length segments of 1 kilometer (km). Every segment inherits the label of the driver who made the trip. For instance, if a driver has MCI, all segments of that driver's trips are labeled as 1.

IV. EXPERIMENTAL EVALUATION

We conducted a series of experiments to evaluate the effectiveness of our proposed feature engineering approach for extracting additional location-based features, in comparison to existing telematics features that are already available in our dataset and commonly used in vehicle trajectory analysis [12], [13], [14], [15], [16], [17], [18], [19] and grid-based approach [33].

- **Location-Based Features:** we employed longitude, latitude, and binary indicators bit1 to bit8. In this study, the geo-regional quad-tree had predefined 4 levels, and each level added 2 bits, which ended in an 8-bit binary code.
- **Telematics features:** includes distance (kilometers), speed (kph), speed over ground (SOG) (kph), and direction (azimuth).
- **Grid-Based features:** are spatial-temporal patterns extracted by mapping segmented trajectories onto a spatial grid and augmenting them through rotation techniques [33].

A. EXPERIMENT LAYOUT

To mitigate potential biases and enhance the model's robustness, we employ down-sampling techniques to balance the dataset between MCI and non-MCI drivers. To assess the generalizability of the proposed model, we conducted experiments on datasets of varying sizes (4 months, 1 year, and 2 years) to improve key performance metrics such as recall, F1 score, and AUC. The layout of our experiments is designed as follows:

B. EVALUATION METRICS

The QBDC problem is fundamentally a binary classification task. According to the real labels provided by the nursing college and predicted data labels, the possible outcomes are categorized as True Positive(TP), True Negative(TN), False Positive(FP), and False Negative(FN). To evaluate the model's performance, we used recall, which measures the ability to identify all actual positive cases; precision, which assesses the accuracy of positive predictions; and the F1-score, which combines both metrics to provide a

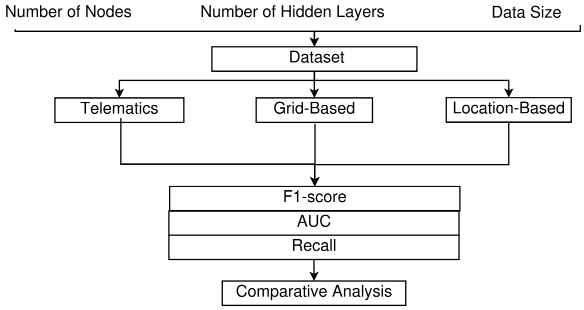


FIGURE 12. **Experimental layout.**

balanced measure of the model's overall effectiveness. The performance of the model was evaluated using the following metrics:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$\text{F1-Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

C. EXPERIMENT RESULTS

We evaluated the proposed approach by comparing it to a baseline method. In the baseline model, we used a Simple Neural Network (SNN) to process telematics features, which includes three fully connected layers with 128, 64, and 32 nodes, respectively. The comparative analysis focused on assessing the impact of (1) dataset size, (2) the number of nodes in the fully connected layers, and (3) the number of layers on the SNN and 2D CNN model performance.

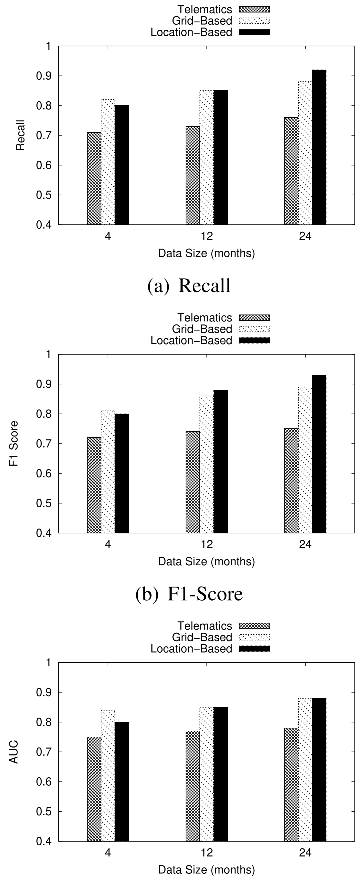
1) EFFECT OF DATA SIZE

We conducted experiments using datasets spanning 4 months, 1 year, and 2 years to assess how varying data sizes influenced the performance of both approaches with telematics, grid-based and location-based features. Figure 13 illustrates the results for Recall, F1-Scores, and AUC across the telematics,grid-based and location-based features with different data sizes.

With increasing dataset sizes (from 4 months to 2 years), the model achieved progressively higher recall, F1-Score, and AUC. A dataset spanning 2 years yielded the highest metrics, demonstrating the model's improved ability to distinguish between MCI and non-MCI drivers. Location-based features consistently achieved superior results compared to telematics and grid-based features, showing that the geo-regional quadtree structure captures critical spatial information, leading to more accurate MCI detection.

2) EFFECT OF NUMBER OF NODES IN 2D CNN

We also examined the impact of reducing the number of nodes in the fully connected (FC) layers of both the 2D CNN and SNN architectures. Table 2 illustrates the original node configurations for the 2D CNN, which used location-based



(a) Recall
(b) F1-Score
(c) AUC

FIGURE 13. **Effect of datasets within 4 months, 1 year, and 2 years for F1-Score, AUC, and Recall across telematics, grid-based, and location-based features.**

TABLE 2. **Number of nodes in the FC layers.**

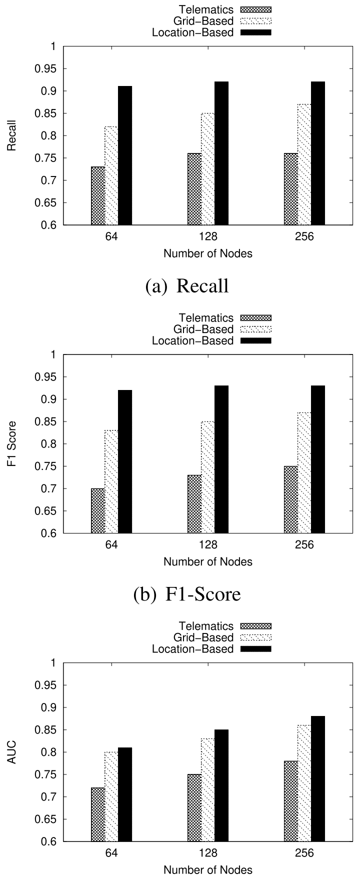
Configuration	FC Layer 1	FC Layer 2	FC Layer 3
Original 2D CNN	256	64	16
Original SNN	128	64	32
Configuration 1	128	32	8
Configuration 2	64	16	4

features, and the SNN, which employed telematics features, with two modified setups labeled Configurations 1 and 2.

The variation in the number of nodes in the fully connected layers did not lead to a significant change in performance metrics, including recall, F1-Score, and AUC. The results remained relatively consistent across different configurations, suggesting that reducing or increasing the number of nodes had minimal impact on the model's ability to classify MCI and non-MCI drivers.

3) EFFECT OF NUMBER OF HIDDEN LAYERS IN 2D CNN

We performed experiments with 1, 2, and 3 hidden layers. Figure 16 presents the Recall, F1-Scores, and AUC for the telematics,grid-based and location-based features across

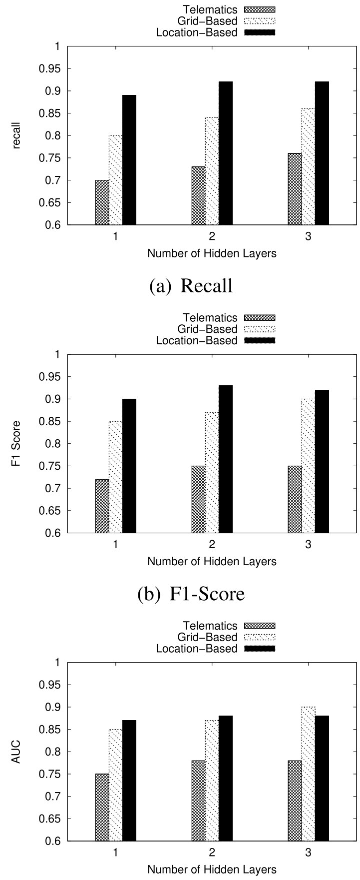


(a) Recall

(b) F1-Score

(c) AUC

FIGURE 14. Effect of the number of nodes for F1-Score, AUC, and Recall across telematics, grid-based and Location-based features.



(a) Recall

(b) F1-Score

(c) AUC

FIGURE 15. Effect of number of Layers on 2D CNN for F1-Score, AUC, and Recall across telematics, grid-based and Location-based features.

different hidden layer configurations. The results showed that adding more hidden layers to the 2D CNN resulted in only minor improvements, with no significant performance gains beyond two layers. This suggests that increasing the model's depth further does not noticeably enhance its classification performance.

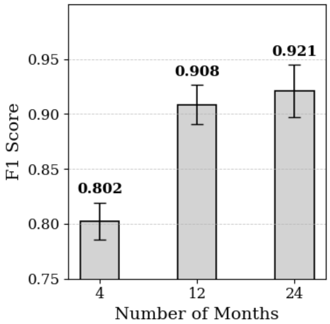
To ensure robust evaluation, we incorporated 5-fold cross-validation into the experimental setup. Figure 16 illustrates the mean F1-scores ($\pm$ standard deviation) for different configurations, highlighting that location-based features derived from the quad-tree consistently outperform telematics and grid-based features. Larger datasets significantly enhance performance, while increasing the number of nodes or hidden layers has minimal impact, indicating that the model is both efficient and effective in leveraging spatial-temporal patterns for MCI detection.

In addition, to compare the performance of the location-based and telematics features in terms of F1 scores, we conducted a paired t-test across 5-fold cross-validation. The location-based features achieved a mean F1 score of 0.9213 ($\pm$0.0188), while the telematics features achieved a mean F1 score of 0.7225 ($\pm$0.0259). The mean difference between the two methods was 0.1986 ($SD = 0.0188$). The paired t-test revealed a statistically significant difference in F1 scores between the two methods ($t = 23.61$, $p = 1.91 \times 10^{-5}$), indicating that the location-based features significantly outperformed the telematics features.

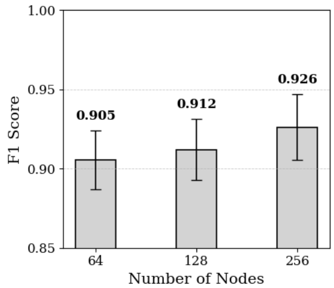
To better illustrate the computational demands of the proposed method, Figure 17 compares the time complexity of geo-regional quad-tree construction and CNN training across different numbers of trips. The results indicate that while quad-tree feature engineering adds preprocessing time, the overall computational complexity remains low due to the $O(n \log n)$ time complexity of quad-tree construction. The approach efficiently scales with data size, making it both computationally feasible and effective in improving classification performance.

V. DISCUSSION

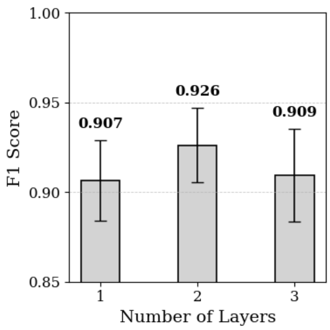
The results of this study highlight the effectiveness of the proposed QBDC approach in detecting MCI in elderly drivers through an analysis of their driving patterns. The hierarchical partitioning of GPS data into regions facilitates extracting meaningful spatial features that significantly enhance model performance in identifying abnormal driving behaviors.



(a) Effect of the data size (months)



(b) Effect of the number of nodes



(c) Effect of the number of layers

FIGURE 16. **Comparison of mean F1-scores (± standard deviation) for different experimental layouts across 5-fold cross-validation.**

The results demonstrate that increasing the dataset size significantly enhances model performance, improving recall, F1-Score, and AUC. Larger datasets allow the model to capture more diverse driving patterns, leading to better classification of MCI and non-MCI drivers. Location-based features derived from the geo-regional quad-tree proved more effective than telematics and grid-based features, emphasizing the importance of spatial information in detecting cognitive impairment. Retaining spatial detail while simplifying the trajectory data helps the model effectively capture potentially abnormal driving patterns, such as road repetitions, long-distance U-turns, or abnormal cyclic patterns. In contrast, variations in the number of nodes and hidden layers in the 2D CNN architecture had minimal impact on performance. The model achieved optimal results with three hidden layers, but increasing complexity

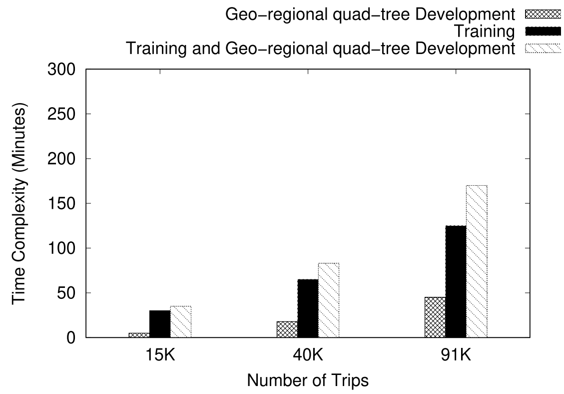


FIGURE 17. **Computational time comparison.**

beyond this did not yield significant improvements. These findings suggest that focusing on data quality and effective feature engineering is more important than adding complexity to the network. Using binary-encoded features from the quad-tree enhanced the interpretability of the model, providing more nuanced insights into driving behaviors. Compared to telematics and grid-based features, the location-based features derived from the geo-regional quad-tree approach consistently demonstrated superior performance, achieving higher recall, F1 scores, and AUC, highlighting their ability to capture critical spatial details essential for distinguishing MCI-related driving behaviors.

VI. CONCLUSION AND FUTURE WORK

This work introduces an innovative method for QBDC to MCI in elderly drivers using quad-tree structures and deep learning techniques. Leveraging the hierarchical spatial partitioning capabilities of geo-regional quad-trees, our approach effectively captures and analyzes both the spatial and temporal dimensions of driving trajectories. Integrating binary encoding for trajectory data with CNNs significantly enhances feature extraction and classification accuracy.

The experimental results validate the effectiveness of our quad-tree based method in identifying abnormal driving patterns associated with MCI. Our study found that MCI drivers exhibit abnormal driving behaviors such as long-distance U-turns, cyclic driving patterns, and road repetition. The quad-tree structure provides a detailed and scalable representation of driving data, addressing the complexities of large-scale spatiotemporal data analysis. This method offers a robust framework for real-time monitoring and early detection of cognitive impairments, contributing to improved road safety and cognitive health monitoring for elderly populations. We are currently collecting video datasets from windshield-mounted cameras to gain deeper insights into driver behavior. In future work, we plan to integrate spatial information with video data to enhance the classification model. Additionally, we aim to incorporate external data sources, such as open weather and road traffic data, to account for factors like traffic conditions, weather, and vehicle type, further improving the model's accuracy.

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