Automatic extraction of relevant road infrastructure using connected vehicle data and deep learning model

by

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ABSTRACT

This thesis presents a novel approach for extracting road infrastructure information from connected vehicle trajectory data, employing geohashing and image classification techniques. The methodology involves segmenting trajectories using geohash boxes and generating image representations of road segments. These images are then processed using YOLOv5 to accurately classify straight roads and intersections. Experimental results demonstrate a high level of accuracy, with an overall classification accuracy of 95%. Straight roads achieve a 97% F1 score, while intersections achieve a F1 score of 90%. These results validate the effectiveness of the proposed approach in accurately identifying and classifying road segments. The integration of geohashing and image classification techniques offers numerous benefits for road network analysis, traffic management, and autonomous vehicle navigation systems. By extracting road infrastructure information from connected vehicle data, a comprehensive understanding of road networks is achieved, facilitating optimization of traffic flow and infrastructure maintenance. The scalability and adaptability of the approach make it well-suited for large-scale datasets and urban areas. The combination of geohashing and image classification provides a robust framework for extracting valuable insights from connected vehicle data, thereby contributing to the advancement of smart transportation systems. The results emphasize the potential of the proposed approach in enhancing road network analysis, traffic management, and autonomous vehicle navigation, thereby expanding the knowledge in this field and inspiring further research.

CHAPTER 1. INTRODUCTION

Transportation planning, traffic management, and the development of autonomous navigation systems heavily rely on the analysis of road infrastructure (1). Obtaining road network information traditionally involves costly and time-consuming manual surveys (2) or the utilization of specialized sensors (3). However, with the proliferation of connected vehicles equipped with GPS-enabled devices (4) and the wealth of driver trajectory data they generate (5), a promising opportunity arises to harness these rich data sources for the automated extraction of road infrastructure information (6). By harnessing GPS data and analyzing driver trajectories, researchers and engineers can uncover valuable insights about road conditions, traffic patterns, and connectivity, which can be instrumental in improving transportation systems, optimizing route planning, enhancing safety measures, and supporting the development of intelligent transportation systems. This automated approach not only saves time and resources but also enables more frequent updates and a more comprehensive understanding of the road network, ultimately leading to more informed decision-making processes and improved overall transportation efficiency.

Use of Connected Vehicle Data in Road Infrastructure Analysis

In recent years, the emergence of connected vehicle technologies has revolutionized the availability of real-time data on traffic patterns and vehicle behavior. Connected vehicles are equipped with a wide array of sensors, such as GPS, accelerometers, gyroscopes, cameras, and radars, along with communication capabilities that enable them to collect and transmit valuable data about their surroundings (11). Exploration of the efficacy of large-scale connected vehicle data in real-time traffic applications by Raghupathi et al. revealed that the connected vehicle data had an average penetration rate of 6.3% (42). These sensors capture crucial information about road conditions, traffic flow, and interactions with other vehicles, presenting an invaluable resource for the automated extraction of road infrastructure information.

Connected vehicles generate vehicle trajectories by continuously recording and updating their position coordinates using GPS technology. The trajectories represent the paths followed by vehicles as they travel through the road network. Each trajectory comprises a sequence of timestamped location points, which provide detailed information about the vehicle's movement patterns, speed, and direction.

In addition to GPS data, connected vehicles make use of various other sensors to capture detailed information about the surrounding environment. For instance, cameras enable the capture of images and video footage of the road, facilitating visual analysis of road infrastructure. Radar sensors provide crucial data on the distance and velocity of objects in the vehicle's vicinity, enabling the detection of nearby vehicles, pedestrians, and other obstacles. Moreover, accelerometers and gyroscopes measure vehicle acceleration, orientation, and tilt, contributing to a comprehensive understanding of vehicle behavior.

By leveraging the rich and diverse data collected from connected vehicles, researchers and analysts can gain valuable insights into road infrastructure. This includes assessing the condition of roads, identifying areas prone to congestion or accidents, evaluating the effectiveness of traffic management strategies, and supporting the development of intelligent transportation systems.

In today's ever-evolving urban landscapes, the efficient and accurate mapping of road infrastructure plays a pivotal role in optimizing transportation systems, bolstering road safety, and ultimately improving the overall mobility experience for drivers and commuters. However, an alarming bottleneck obstructs progress – the time-consuming, labor-intensive process of manually identifying intersections. In the case of Iowa alone, where a staggering 166,000 intersections await discovery, each taking an average of 3 minutes for human groups to locate and collect data, a critical problem arises. This inefficiency restricts the creation of a comprehensive and up-to-date database for the entire US road network, hindering smarter, data-driven transportation management.

Currently, data collection for intersection identification is carried out through visual inspection, utilizing roadway images and aerial images based on the Model Inventory of Roadway Elements – MIRE 2.0. While this data collection method has yielded valuable insights, it has proven to be resource-intensive and time-consuming. Although this represents a significant effort, it falls short of covering the entirety of the vast road network. To address these limitations and enhance the efficiency of intersection identification, this thesis proposes a novel approach based on the utilization of connected vehicle data and a deep learning model. By harnessing the power of advanced data analytics and machine learning, the proposed method aims to detect intersections without relying on all the data details, offering the potential to significantly reduce the time and resources required for comprehensive road infrastructure mapping.

The Model Inventory of Roadway Elements – MIRE 2.0 remains a valuable resource, providing crucial insights and supporting data-driven safety decision making. However, as the transportation landscape continues to evolve, embracing innovative techniques like connected vehicle data and deep learning models can pave the way for a more streamlined and data-efficient transportation management system, laying the foundation for smarter and safer road networks.

While OpenStreetMap (OSM) provides a valuable repository of crowd-sourced data, its reliance on manual contributions poses inherent limitations. The constantly changing road infrastructure demands a more dynamic approach to ensure timely updates and accurate representation. This pressing need for a holistic, automated solution has led to the pioneering integration of connected vehicle data and cutting-edge deep learning models for the automatic extraction of relevant road infrastructure information.

By harnessing the rich insights collected from connected vehicles, we can dramatically expedite the process of identifying intersections, breaking free from the shackles of time-consuming human efforts. This technological leap holds the promise of revolutionizing the road infrastructure mapping landscape. Not only will it create a comprehensive database for the United States, encompassing every intersection with unprecedented accuracy and real-time updates, but it will also serve as a vital blueprint for countries currently grappling with the lack of a centralized intersection identification system.

This thesis embarks on a journey to explore the potential of Automatic Extraction of Relevant Road Infrastructure using Connected Vehicle Data and Deep Learning. The fusion of these innovative technologies will not only unlock the speed and efficiency needed to address the intersection mapping challenge but also pave the way for a safer, more adaptive, and interconnected transportation ecosystem. From empowering city planners and traffic management authorities with real-time infrastructure updates to revolutionizing traffic flow optimization and emergency response systems, the implications of this groundbreaking research reach far beyond its immediate application.

With the vision of a smarter, data-driven future for transportation, this work endeavors to break through barriers and set new standards, presenting a transformational approach to road infrastructure mapping, and driving us towards a more connected, safer, and sustainable world.

Proposed Approach: Geohashing and Image Classification with YOLOv5

In this thesis, we propose an innovative approach that combines geohashing and image classification with the YOLOv5 algorithm (7)(8) to automatically identify different types of road segments from vehicle trajectories. Our method builds upon the spatial indexing technique of geohashing and leverages the powerful capabilities of YOLOv5 for accurate and efficient road segment identification.

To begin, we employ geohashing as a spatial indexing technique to divide the geographic space into small rectangular grid cells, commonly referred to as geohash boxes (9). This approach allows us to effectively manage and analyze the large volumes of driver trajectories. By converting the trajectories into images using geohash boxes, we create a visual representation that can be utilized for subsequent analysis (7).

By utilizing the geohash box images, we can then apply the state-of-the-art image classification techniques of the YOLOv5 algorithm. YOLOv5 is a deep learning model that excels in object detection and classification tasks, making it well-suited for our road segment identification purposes (8).

With the YOLOv5 algorithm, we can effectively detect and categorize various road segments, with a specific focus on identifying straight roads and intersections. By leveraging the information captured in the geohash box images, YOLOv5 enables us to accurately determine the presence and location of different road segment types within the trajectories (8).

By combining geohashing and image classification with YOLOv5, our proposed approach provides a robust and efficient solution for automatically identifying road segments from vehicle trajectories. This methodology not only allows for the automated extraction of road infrastructure information but also opens possibilities for further analysis and applications, such as optimizing transportation planning, enhancing traffic management strategies, and supporting the development of autonomous navigation systems.

Research Objective: Feasibility and Effectiveness of Automated Road Infrastructure Extraction

The primary goal of this research is to demonstrate the feasibility and effectiveness of our approach for automatic road infrastructure extraction (10). By utilizing the rich spatial and temporal information present in driver trajectories, we aim to overcome the limitations of traditional data collection methods and provide a scalable solution for road network analysis (6). Our approach leverages advanced machine learning algorithms to process the vast amounts of trajectory data available from GPS-enabled devices and extract meaningful information about road infrastructure characteristics. This automated extraction process not only saves time and resources but also enables more frequent updates and a more comprehensive understanding of the road network.

Moreover, our research seeks to showcase the potential impact of this approach on various applications in the transportation domain. One key application is traffic management, where accurate and up-to-date road infrastructure information plays a critical role in optimizing traffic flow, detecting congestion, and improving overall transportation efficiency. By automatically extracting road infrastructure features from driver trajectories, transportation agencies and authorities can make informed decisions about traffic signal timing, lane configurations, and road network improvements.

Additionally, our research aims to contribute to urban planning efforts. The automated extraction of road infrastructure information can provide valuable insights for urban planners, helping them understand the existing road network layout, identify areas in need of improvement or expansion, and support the development of sustainable and efficient urban transportation systems.

Furthermore, our approach has implications for autonomous vehicle navigation systems. Accurate and detailed road infrastructure information is essential for autonomous vehicles to navigate safely and efficiently. By automatically extracting road geometry, lane configurations, and other infrastructure features, our research can contribute to the advancement of autonomous navigation algorithms and enhance the overall reliability and performance of autonomous vehicles.

This research seeks to demonstrate the feasibility and effectiveness of our approach for automatic road infrastructure extraction. Through the analysis of driver trajectories and the application of advanced machine learning algorithms, we aim to provide a scalable solution that overcomes the limitations of traditional data collection methods. The potential benefits of our approach span across various applications, including traffic management, urban planning, and autonomous vehicle navigation systems, ultimately leading to improved transportation systems and enhanced mobility for individuals and communities.

Structure of the Thesis

In the following sections, we will discuss the related works, methodology in detail, starting with an overview of geohashing and its application to clip driver trajectories onto a plot. Subsequently, we will describe the image classification process utilizing YOLOv5 to detect and classify road segments, specifically focusing on straight roads and intersections. Experimental results will be presented to validate the effectiveness and accuracy of our approach, followed by a discussion of potential applications and future research directions.

CHAPTER 2. LITERATURE REVIEW

Road infrastructure extraction from vehicle trajectories using Geohashing and image classification with YOLOv5 is a pivotal topic within the realm of transportation studies. The analysis of road infrastructure and the detection of road intersections have emerged as fundamental components for various applications, including but not limited to traffic management, autonomous vehicle navigation, and comprehensive road network analysis (11). Over the years, a multitude of studies have been conducted to tackle the intricate challenges inherent in this domain, employing diverse methodologies such as vehicle trajectory data analysis, GPS traces, and cutting-edge algorithms. Thus, in the following literature review, we endeavor to present a comprehensive overview of the significant contributions made by relevant research in this field. By delving into the extensive body of work conducted thus far, we aim to shed light on the progress achieved, identify gaps, and elucidate potential avenues for future exploration and improvement in the realm of road infrastructure extraction from vehicle trajectories, with a particular emphasis on leveraging Geohashing techniques in conjunction with image classification utilizing the YOLOv5 framework.

Firstly, Fathi and Krumm (12) proposed an automated approach that tackles the challenge of detecting road intersections from GPS traces. Their method not only offers a cost-effective and efficient solution for map generation but also leverages GPS data from regular vehicles, ensuring scalability and real-time updates. By training a shape descriptor on intersection examples, their algorithm successfully identifies potential intersections within the GPS data. These detected intersections are then connected through vehicle traces and refined using associated GPS data, resulting in accurate intersection detection. The study's evaluation compared the approach against a known road network, demonstrating its effectiveness in detecting intersections and estimating road lengths.

This work by Fathi and Krumm significantly contributes to the advancement of road infrastructure extraction techniques. By providing an automated solution that utilizes GPS data from everyday drivers, it addresses the need for alternative and more accessible methods compared to specialized surveys. This approach holds great promise in terms of scalability and real-time updates, which are crucial for maintaining up-to-date maps.

In another study, Ahmed et al. (13) conducted a comprehensive evaluation and comparison of map construction algorithms, focusing on the utilization of vehicle tracking data. Their research aimed to assess the effectiveness of different algorithms in generating accurate and reliable maps based on vehicle trajectory information. The evaluation considered various factors, including the quality of input data, algorithm complexity, and resulting map quality.

Ahmed et al. (13) compared multiple map construction algorithms using real-world vehicle tracking data, analyzing factors such as road network connectivity, accuracy of road segment placement, and the ability to handle different road types and features. Their analysis and comparison provide valuable insights into the strengths and weaknesses of each approach. To measure the accuracy of road segment placement and the overall quality of the generated maps, metrics such as precision, recall, F-measure, and accuracy were employed. The study aims to guide researchers and practitioners in selecting suitable map construction algorithms based on specific requirements and the characteristics of the available vehicle tracking data.

The themes that emerge from these studies revolve around the automation and efficiency of road infrastructure extraction techniques. Both Fathi and Krumm's (12) work and Ahmed et al.'s (13) research emphasize the importance of utilizing GPS data and vehicle tracking information to generate accurate and up-to-date maps. By automating the detection of road intersections, Fathi and Krumm contribute to cost-effectiveness and scalability, while Ahmed et al.'s evaluation of map construction algorithms provides insights into improving map quality and accuracy.

Despite these advancements, some debates and gaps can be identified. For instance, while Fathi and Krumm's approach focuses on detecting intersections, other elements of road infrastructure extraction, such as the number of lanes and straight roads, may require further exploration. Additionally, the evaluation of map construction algorithms by Ahmed et al. primarily focuses on quantitative metrics, but qualitative aspects such as the visual representation or user-friendliness of the generated maps could be valuable considerations.

In conclusion, the studies by Fathi and Krumm (12) and Ahmed et al. (13) have provided significant insights into the automation, efficiency, and evaluation of road infrastructure extraction techniques. Fathi and Krumm's work introduces a promising automated solution for detecting road intersections using GPS data, addressing the need for cost-effective and scalable methods. Ahmed et al.'s research, on the other hand, offers a comprehensive evaluation of map construction algorithms, aiding in the selection of suitable approaches based on specific requirements. As we delve further into the literature, additional studies will be explored to uncover other aspects of road infrastructure extraction, debate various methodologies, and identify remaining gaps in the field. Let us now proceed to the subsequent sections to delve deeper into the existing research and broaden our understanding of this evolving domain.

Karagiorgou and Pfoser (14) conducted a study on road network generation using vehicle tracking data, aiming to overcome the limitations of traditional map generation methods. By analyzing vehicle trajectories, they developed an approach that effectively captured road connectivity and attributes. Through evaluation and comparison with existing road network data, their research demonstrated the potential of vehicle tracking data in accurately extracting road network information. This study contributes to the field by exploring the utilization of vehicle tracking data for road network generation and provides valuable insights for future research in this area.

In another study, Wang et al. (15) focused on the automatic detection of intersections and traffic rules through the analysis of motor-vehicle GPS trajectories. Their research aimed to develop an automated approach that extracts valuable information from GPS data to identify intersections and traffic rules. By analyzing trajectory patterns and employing data mining techniques, the authors aimed to enhance the understanding of traffic dynamics and contribute to transportation planning and management.

Their study employed data mining techniques to extract meaningful information from GPS trajectories. Wang et al. (15) developed algorithms that automatically identified intersections and detected traffic rules based on analyzed trajectory patterns. These algorithms considered factors such as trajectory proximity to specific geographic locations, frequency of trajectory crossings, and consistency of movements at certain locations. By leveraging these patterns, the researchers aimed to infer the presence of intersections and deduce associated traffic rules.

To evaluate their algorithms, real-world motor-vehicle GPS trajectory data was used. The authors assessed the accuracy and effectiveness of their approach by comparing the detected intersections and traffic rules with ground truth data. The study successfully demonstrated the feasibility and reliability of automatic intersection and traffic rule detection through the analysis of motor-vehicle GPS trajectories.

The themes that emerge from these studies revolve around the utilization of vehicle tracking data for road network generation and the extraction of valuable information from GPS trajectories. Both studies contribute to overcoming the limitations of traditional methods and offer potential solutions for transportation planning and management. However, debates and gaps exist regarding the scalability and generalizability of these approaches, consideration of varying geographic contexts, and integration of other relevant data sources to improve accuracy and reliability. These areas present opportunities for future research to further advance the field of road infrastructure extraction using vehicle tracking data.

In conclusion, the studies by Karagiorgou and Pfoser (14) and Wang et al. (15) have shed light on the utilization of vehicle tracking data for road network generation and the extraction of valuable information from GPS trajectories. Karagiorgou and Pfoser's work demonstrates the potential of vehicle tracking data in accurately capturing road connectivity and attributes, providing an alternative to traditional map generation methods. On the other hand, Wang et al.'s research presents an automated approach that leverages GPS data to detect intersections and traffic rules, offering valuable insights for transportation planning and management. As we delve further into the literature, additional studies will be explored to uncover other aspects of road infrastructure extraction, address debates surrounding scalability and generalizability, consider varying geographic contexts, and explore the integration of complementary data sources. Let us now proceed to the subsequent sections to broaden our understanding of the evolving field.

In a related study, Zhang et al. (16) focused on the automatic construction of road networks using massive GPS trajectory data. Their research aimed to develop an efficient and accurate approach for generating road networks based on the analysis of extensive GPS trajectory data. By leveraging the abundance of trajectory information, the authors aimed to improve the road network construction process, which is crucial for various transportation applications.

The method proposed by Zhang et al. (16) consisted of multiple steps, including data preprocessing, trajectory segmentation, road segment extraction, and network construction. These steps aimed to identify and extract road segments from GPS trajectories and connect them to form a comprehensive road network. The method considered factors such as trajectory density, spatial proximity, and temporal continuity to enhance the accuracy of road segment extraction and network construction.

To evaluate their approach, real-world GPS trajectory data was utilized. Zhang et al. (16) compared the automatically constructed road network with existing road maps and assessed the accuracy and completeness of the generated network. The evaluation aimed to demonstrate the effectiveness and reliability of the proposed method in automatically constructing road networks from massive GPS trajectory data.

The themes that emerge from the studies revolve around the utilization of GPS trajectory data for road network construction and enhancement. These studies contribute to advancing the field by offering automated approaches that leverage the abundance of trajectory information. However, there are still debates and gaps to be addressed, such as the scalability of these methods to handle large-scale datasets, the generalizability across different geographic regions, and the integration of additional contextual information to further improve the accuracy and completeness of road network generation.

Yang et al. (17) introduced an innovative method for generating lane-based intersection maps using crowdsourced big trace data. Their research aimed to harness the collective intelligence of crowdsourced data to extract detailed information about lane-based intersections, which is valuable for various transportation applications. The study by Yang et al. makes a notable contribution to the field; nevertheless, upon careful examination, some methodological considerations and research gaps become apparent, suggesting areas for improvement in future studies.

The method proposed by Yang et al. (17) involves several steps, including trace preprocessing, intersection extraction, lane detection, and map generation. Although the authors provide a clear outline of these steps, further evaluation is necessary to assess their effectiveness and limitations. Methodological issues, such as potential biases in the crowdsourced data and the accuracy of spatial clustering and lane detection algorithms, should be carefully considered. Future research could explore alternative methods or address these limitations to enhance the reliability and robustness of the approach.

To evaluate the method, large-scale crowdsourced trace data was utilized, which is commendable for its real-world applicability. However, it is important to critically examine the limitations of this approach. Potential biases in the crowdsourced data, such as uneven representation or varying data quality, may impact the accuracy and generalizability of the results. Additionally, while comparing the generated lane-based intersection maps with ground truth data provides an initial assessment of accuracy and completeness, further validation is needed in diverse geographic contexts and under different traffic conditions.

Despite these considerations, the research by Yang et al. (17) represents a significant step forward in transportation applications by presenting a method for generating lane-based intersection maps using crowdsourced big trace data. Leveraging the collective intelligence of multiple vehicle traces offers valuable information for improved transportation planning and management. The evaluation using real-world crowdsourced data provides initial evidence of the method's effectiveness, but future studies should aim to replicate and extend these findings.

In conclusion, while Yang et al.'s (17) study contributes to the field of transportation applications, a critical analysis reveals methodological considerations and research gaps that need to be addressed. Future studies should focus on overcoming these limitations, exploring alternative methods, and conducting comprehensive evaluations to enhance the reliability and applicability of generating accurate and detailed lane-based intersection maps using crowdsourced big trace data.

As we proceed with the literature review, it is important to explore additional studies that delve into diverse aspects of road infrastructure extraction. These studies can provide alternative methodologies, address challenges in scalability and generalizability, and help identify potential gaps in the existing research. By exploring these studies, we can develop a comprehensive understanding of the evolving field and gain valuable insights for future advancements.

One such study conducted by Ruhhammer et al. (18) focused on automated intersection mapping by leveraging crowd trajectory data. Their proposed method (Ruhhammer et al., 18) consisted of three key steps: data preprocessing, trajectory clustering, and intersection detection. Although these steps were outlined in their study, evaluating their effectiveness and limitations is crucial. Methodological considerations such as potential biases in crowd trajectory data and the accuracy of trajectory clustering algorithms must be carefully examined. Future research could explore alternative methods or address these limitations to enhance the reliability and robustness of the approach.

In evaluating their proposed method, Ruhhammer et al. (18) utilized real-world crowd trajectory data and compared the generated intersection maps with ground truth data. While this evaluation provided initial insights into the accuracy and completeness of the extracted intersection structures, further investigation is necessary to validate the results across diverse geographic contexts and under different traffic conditions. Additionally, it is essential to critically examine the limitations of crowd trajectory data, including potential biases and variations in data quality, which may affect the reliability and generalizability of the findings.

The findings presented by Ruhhammer et al. (18) make a significant contribution to the field of automated intersection mapping and offer valuable insights into the utilization of crowd trajectory data for this purpose. Their method presents a promising approach for accurately identifying and mapping the spatial layout of intersections, which holds practical implications for transportation planning, traffic management, and urban development. However, future studies should aim to address the methodological considerations and research gaps identified, and further explore the potential limitations of the approach.

Wu et al. (19) presented a method for detecting road intersections from GPS traces with low sampling rates. Their aim was to identify and extract intersection points from coarse-grained GPS data. To achieve their goal, Wu et al. (19) employed a method consisting of two primary steps: data preprocessing and intersection detection. In the data preprocessing step, GPS traces were transformed into a grid-based representation to reduce data density and facilitate subsequent analysis. While this preprocessing technique may effectively reduce computational complexity, potential limitations should be addressed. For instance, the impact of grid size and resolution on intersection detection accuracy and the potential loss of important spatial information during the transformation process should be carefully evaluated.

Furthermore, a density-based clustering algorithm was applied to identify clusters of GPS points that indicate potential road intersections. The authors incorporated distance thresholds and density parameters to enhance intersection detection accuracy. However, further investigation is needed to assess the robustness and reliability of the clustering algorithm, particularly in scenarios with varying traffic conditions, road geometries, and intersection complexities.

To evaluate the effectiveness of their method, Wu et al. (19) utilized real-world GPS trace data and compared the detected intersections with ground truth data. While this evaluation provides initial evidence of accuracy, comprehensive validation in diverse geographic contexts and under different sampling rates is necessary to establish the method's reliability and generalizability.

In a separate study, De Fabritiis et al. (20) conducted research on traffic estimation and prediction using real-time floating car data. Their approach aimed to leverage data collected from moving vehicles to accurately estimate and predict traffic conditions. De Fabritiis et al. (20) performed real-time analysis of speed profiles and positions of floating cars, utilizing statistical methods to estimate traffic flow parameters, and forecast future traffic conditions. While statistical methods can provide valuable insights, further investigation is needed to assess the sensitivity of the approach to various traffic scenarios and the accuracy of predictions over longer time horizons. Factors such as traffic density, speed variations, and congestion levels were considered; however, additional research is needed to determine the most influential factors and their interplay in different traffic contexts.

The evaluation of De Fabritiis et al.'s (20) proposed approach using real-time floating car data demonstrated its effectiveness in generating reliable traffic estimations. However, further studies should focus on validating the approach in different urban environments, considering variations in road networks, traffic patterns, and driving behaviors.

In summary, Wu et al. (19) proposed a method for detecting road intersections from low-resolution GPS traces, utilizing clustering techniques and data preprocessing. While their approach shows promise, methodological considerations such as the impact of data preprocessing and the robustness of the clustering algorithm need to be addressed. Similarly, De Fabritiis et al. (20) contributed to traffic estimation and prediction using real-time floating car data, but further research is needed to validate and refine their approach across diverse urban environments and for longer-term predictions. These studies provide valuable insights into the extraction of road infrastructure information from GPS traces and the utilization of floating car data for traffic estimation and prediction. Future research should aim to address the identified methodological considerations and explore additional themes such as low-resolution GPS data analysis, traffic pattern recognition, and real-time traffic management to advance our understanding of these topics.

Deng et al. (21) presented a novel methodology for generating accurate urban road intersection models from low-frequency GPS trajectory data. Their research aimed to overcome the limitations associated with such data and extract detailed intersection models that capture the intricate structure of urban road networks. The proposed methodology by Deng et al. (21) consists of several key steps, including data preprocessing, trajectory segmentation, intersection identification, and model construction. While these steps provide a clear framework, further critical evaluation is necessary to assess the effectiveness and limitations of each stage. Methodological problems, such as the impact of noise or outliers in the low-frequency GPS trajectory data, should be carefully considered. Additionally, the accuracy and reliability of techniques like trajectory clustering and graph-based analysis employed for intersection identification and model construction require thorough investigation and comparison with alternative approaches.

To evaluate the effectiveness and reliability of their method, Deng et al. (21) conducted experiments using real-world low-frequency GPS trajectory data collected from urban environments. While the use of real-world data is commendable, it is important to critically examine the limitations of this approach. Potential biases in the data collection process, such as uneven spatial distribution or incomplete trajectory data, may affect the accuracy and generalizability of the generated intersection models. Furthermore, the comparison with ground truth data provides an initial assessment; however, further investigations are needed to validate the results in diverse urban contexts and consider the impact of varying traffic conditions.

Despite these methodological considerations, the research by Deng et al. (21) presents a comprehensive methodology for generating accurate urban road intersection models from low-frequency GPS trajectory data. By addressing the limitations associated with this type of data, valuable information about urban road networks can be extracted, facilitating transportation planning and management. The evaluation using real-world data provides initial evidence of the method's effectiveness; however, future studies should aim to replicate and extend these findings to enhance the reliability and applicability of generating intersection models from low-frequency GPS trajectory data.

Moving on to another study, Karagiorgou et al. (22) conducted research on segmentation-based road network construction. Their study aimed to develop an automated method for constructing road networks by segmenting GPS trajectory data. The proposed method by Karagiorgou et al. (22) involved several steps, including trajectory segmentation, road segment extraction, and network construction. While the authors provide a description of these steps, further critical evaluation is necessary to assess the effectiveness and limitations of each stage. Methodological problems, such as the robustness of the clustering algorithms employed and the potential impact of varying data quality in the trajectory data, should be carefully considered. Future research could explore alternative segmentation approaches or address these limitations to enhance the accuracy and reliability of road segment extraction and network construction.

To evaluate the proposed method, real-world GPS trajectory data was utilized. Although the use of real-world data is commendable, it is important to critically examine the limitations associated with it. Factors such as data sparsity or biases in the trajectory data may affect the accuracy and generalizability of the constructed road networks. Additionally, the comparison of the constructed road networks with existing road maps provides an initial assessment of accuracy and completeness; however, further investigation is needed to validate the results across diverse geographic areas and under different driving conditions.

Despite these methodological considerations, the research by Karagiorgou et al. (22) represents an important step forward in the automated construction of road networks using GPS trajectory data. By leveraging the spatial and temporal characteristics of the trajectories, valuable information about road segments and their connectivity can be extracted, facilitating improved transportation planning and navigation. The evaluation using real-world GPS trajectory data provides initial evidence of the method's effectiveness, but future studies should aim to replicate and extend these findings.

Shifting focus to another study, Xie et al. (23) introduced a method for detecting road intersections from GPS traces utilizing the longest common subsequence (LCS) algorithm. Their objective was to identify intersections by analyzing the similarity between GPS traces and identifying common subsequences that indicate the presence of intersections.

The proposed method by Xie et al. (23) consisted of two main steps: data preprocessing and intersection detection. In the data preprocessing step, GPS traces were preprocessed to remove noise and outliers. Subsequently, the LCS algorithm was applied to compare GPS point subsequences and identify the longest common subsequences corresponding to road intersections. The approach incorporated distance thresholds and similarity measures to enhance the accuracy of intersection detection.

To evaluate the effectiveness of their method, Xie et al. (23) used real-world GPS trace data. They compared the detected intersections with ground truth data and assessed the accuracy of the extracted intersection points. The evaluation aimed to demonstrate the efficacy of the LCS algorithm in detecting road intersections from GPS traces.

In a similar vein, Li et al. (24) focused on the extraction of road intersections from GPS traces based on the dominant orientations of roads. Their research aimed to identify intersections by analyzing the directional characteristics of GPS traces and accurately detecting intersections by considering the dominant orientations of roads.

Li et al.'s (24) approach involved multiple steps, including data preprocessing, dominant orientation extraction, and intersection detection. Through these steps, the authors aimed to extract the dominant orientations of road segments from GPS traces and identify intersections based on the intersection of dominant orientations. Statistical measures and orientation analysis were employed to improve the accuracy of intersection detection.

To evaluate their method, Li et al. (24) conducted experiments using real-world GPS trace data. They compared the extracted intersections with ground truth data and assessed the accuracy of the detected intersection points. The evaluation aimed to demonstrate the effectiveness of the dominant orientation-based approach in extracting road intersections from GPS traces.

In summary, Xie et al. (23) proposed a method based on the LCS algorithm, while Li et al. (24) focused on dominant orientation-based extraction of road intersections from GPS traces. Both studies aimed to enhance the accuracy and reliability of intersection detection by analyzing GPS trace data. The evaluations conducted in these studies demonstrated the effectiveness and feasibility of their respective approaches in detecting and extracting road intersections from GPS traces.

In a study by Tang et al. (25), a novel method was presented to accurately extract road intersections and construct intersection models using vehicle trajectory data. By analyzing spatiotemporal patterns in these trajectories, the authors were able to identify the locations and connectivity of road intersections. Their method involved data preprocessing, intersection identification, and intersection model construction. Through processing the vehicle trajectory data, clusters of trajectories representing road intersections were identified, and intersection models were constructed based on the connectivity between these clusters.

To evaluate the effectiveness of Tang et al.'s (25) method, real-world vehicle trajectory data was compared with the constructed intersection models as ground truth. This evaluation aimed to demonstrate the method's reliability in road intersection construction from vehicle trajectory data.

Similarly, Wang et al. (26) proposed a novel approach for generating accurate routable road maps from vehicle GPS traces. Their research aimed to transform raw GPS traces into road networks essential for navigation and route planning purposes. By analyzing the GPS traces and their spatial relationships, they aimed to construct road networks with precise topology and connectivity. Their approach involved data preprocessing, road segment extraction, and network construction. During preprocessing, noise and outliers were removed from the GPS traces, road segments were then extracted based on the spatial and temporal characteristics of the GPS traces, and finally, these road segments were connected to form a routable road network.

The proposed approach by Wang et al. (26) was evaluated using real-world vehicle GPS trace data, comparing the generated road maps with ground truth data. The evaluation aimed to demonstrate the effectiveness and feasibility of the approach in generating routable road maps from vehicle GPS traces. However, further research is needed to address scalability, generalizability, and the integration of diverse data sources, which are significant research gaps in this domain.

Both Tang et al. (25) and Wang et al. (26) made valuable contributions to improving the accuracy and usability of road networks derived from vehicle trajectory data. Their evaluations demonstrated the effectiveness and feasibility of their respective approaches in constructing road intersections and generating routable road maps from vehicle GPS traces.

Moving forward, Xie et al. (27) proposed a method for detecting intersections from GPS traces by employing trajectory similarity analysis. Their approach involved comparing GPS trajectories to identify common patterns and infer the presence of intersections. By utilizing density-based clustering and trajectory similarity analysis, the authors aimed to improve the accuracy of intersection detection. The proposed method was evaluated using real-world GPS trace data, comparing the detected intersections with ground truth data. This evaluation aimed to demonstrate the effectiveness of trajectory similarity analysis in detecting road intersections from GPS traces.

Additionally, Chen et al. (28) presented an approach for enhancing road intersection detection from low-frequency GPS trajectory data. Their method involved extending the classification course by considering additional features and employing advanced classification techniques. By analyzing the spatial and temporal characteristics of GPS trajectories, they aimed to improve the reliability of identifying road intersections. The approach included data preprocessing, feature extraction, and classification. Real-world low-frequency GPS trajectory data was used to evaluate the effectiveness of the proposed approach, comparing the detected intersections with ground truth data. This evaluation aimed to demonstrate the improvements achieved by the extended classification course in detecting road intersections from low-frequency GPS trajectory data.

In summary, Xie et al. (27) proposed a method for detecting intersections from GPS traces using trajectory similarity analysis, while Chen et al. (28) focused on improving road intersection detection from low-frequency GPS trajectory data by extending the classification course. Both studies aimed to enhance the accuracy and reliability of intersection detection by analyzing GPS trajectory data. The evaluations conducted in these studies demonstrated the effectiveness and feasibility of the respective approaches in detecting road intersections from GPS traces. However, to further advance this field, additional research is required to address methodological challenges, explore research gaps, and facilitate the development of more robust and scalable techniques.

To continue our exploration of the evolving field, Wang et al. (29) presented a research study on automatic intersection and traffic rule detection by mining motor-vehicle GPS trajectories. Their objective was to develop a method that could automatically detect intersections and extract traffic rules from GPS trajectory data of motor vehicles. By analyzing the spatiotemporal patterns of GPS trajectories, the authors aimed to identify intersections and uncover the underlying traffic rules.

The proposed method consisted of several steps, including data preprocessing, intersection detection, and traffic rule extraction. In the data preprocessing step, the GPS trajectory data of motor vehicles underwent processing to remove noise and outliers. Next, an intersection detection algorithm was applied to identify the locations of intersections based on the convergence of trajectories. Subsequently, traffic rules were extracted by analyzing the behavior of vehicles at the identified intersections, such as right-of-way rules and lane usage patterns.

To evaluate the effectiveness of their method, Wang et al. used real-world motor-vehicle GPS trajectory data. They compared the detected intersections and extracted traffic rules with ground truth data and assessed the accuracy of the detection results. The evaluation aimed to demonstrate the capability of the proposed method in automatically detecting intersections and extracting traffic rules from motor-vehicle GPS trajectories.

In summary, Wang et al. (29) proposed a method for automatic intersection and traffic rule detection by mining motor-vehicle GPS trajectories. The study aimed to enhance the understanding of road networks and traffic rules by leveraging GPS trajectory data. The evaluations conducted in this study demonstrated the effectiveness and feasibility of the proposed method in automatically detecting intersections and extracting traffic rules from motor-vehicle GPS trajectories.

In conclusion, the literature reviewed in this thesis has significantly contributed to the analysis of road infrastructure and the detection of road intersections using driver trajectory data. These studies have employed a range of techniques, including angle-based analysis, clustering, sequence matching, and network analysis, demonstrating the potential of GPS traces for precise and efficient road network generation.

However, it is crucial to recognize that driver trajectory data is not the only valuable resource for intersection detection. Human annotations, in the form of crowd-sourced data, have proven to be another powerful means of identifying intersections in road networks (43). Crowdsourcing platforms and community-driven mapping initiatives, such as OpenStreetMap (OSM), have become instrumental in gathering ground-level information about roads, intersections, and other traffic-related features.

Satellite imagery has emerged as a valuable resource in the field of road infrastructure analysis, providing a broader perspective and capturing vast geographical areas at high resolutions (44). By leveraging satellite imagery alongside driver trajectory data, researchers can obtain a more comprehensive view of road networks, enriching the dataset for intersection identification. This fusion of diverse data sources presents a compelling opportunity to address certain challenges faced by individual techniques, such as data sparsity and gaining insights into the temporal dynamics of road infrastructure. The integration of satellite imagery into intersection detection frameworks promises to add depth and accuracy, opening new horizons for smarter and more adaptive transportation systems.

Moreover, the integration of satellite imagery alongside driver trajectory data and human annotations offers a holistic approach to intersection detection. Satellite imagery provides a high-level view of road networks, capturing extensive geographic regions with exceptional detail. This complements the precision of driver trajectory data and enriches the dataset for intersection identification.

By leveraging these complementary data sources, researchers can overcome certain challenges faced individually by each technique. Crowd-sourced data can help address data sparsity, especially in less-traveled or remote areas, while satellite imagery can offer insights into the temporal dynamics of road infrastructure.

Nonetheless, it is essential to acknowledge that each approach brings its own set of complexities, and integrating these diverse data types requires careful consideration of data processing and fusion techniques. Further research in this area should focus on developing robust methodologies that effectively combine human annotations, satellite imagery, and driver trajectory data to create a comprehensive and accurate database for road intersections.

As the field of road infrastructure analysis progresses, adopting a multi-faceted approach that embraces the potential of human annotations, satellite imagery, and connected vehicle data will foster more comprehensive and intelligent intersection detection systems. Overcoming the remaining challenges of data sparsity, temporal dynamics, and scalability through interdisciplinary research will pave the way for a more resilient and data-rich foundation for smarter, data-driven transportation systems of the future.

Building upon the advancements in this field, this paper introduces a novel method that revolutionizes the extraction of road infrastructure information from driver trajectories. By leveraging geohashing and image classification techniques, our approach surpasses existing methods in terms of data density, accuracy, and scalability. The use of geohash boxes for trajectory clipping and YOLOv5 for image processing allows for enhanced performance and robustness.

Through rigorous experimentation, our proposed method has proven its effectiveness and accuracy. The results obtained unequivocally demonstrate its potential for improving road network analysis, traffic management, and autonomous vehicle navigation systems. By incorporating our approach, researchers and practitioners can overcome the limitations of existing methods and unlock new opportunities for leveraging driver trajectory data in transportation studies.

Below is a comprehensive table (Table 1. Comparing map generation algorithms.) examining various map generation algorithms in the context of related works. The table provides an analysis of the advantages and disadvantages associated with each algorithm. The algorithms are categorized below. The descriptions and explanations of these algorithms are primarily based on the paper titled " A comparison and evaluation of map construction algorithms using vehicle tracking data" by Ahmed, Mahmuda, et al. (13):

- Point clustering:

  Algorithms in this category involve the clustering of a set of points to create street segments that form a cohesive street map. The input for these algorithms can consist of either all the raw input measurements or a dense sample of the input tracks. The input tracks are typically continuous curves derived from interpolating between measurements, often using piecewise-linear interpolation.

- Incremental Track Insertion:

  Algorithms in this category build a street map by gradually inserting tracks into an initially empty map. These algorithms often incorporate map-matching techniques and utilize distance measures and vehicle headings to determine where tracks should be added or removed during the incremental construction process of the map.

- Intersection Linking:

The intersection linking approach, while related to point clustering, focuses specifically on identifying the intersection vertices within the street map. In the first step, the algorithm detects these intersection points, and in the second step, it connects these intersections by identifying appropriate street segments to link them together.

- Other:

  This category of algorithms concentrates on generating road intersection models using low-frequency GPS trajectory data. The algorithms extract road intersections by analyzing the dominant orientations of roads present in the data.

Table 1. Comparing map generation algorithms.

Algorithm Category	**Pros**	**Cons**	**Authors**
Point Clustering	1. Effective clustering, consistent representation in dynamic environments, and clustering and extraction of road segments.	1. Potential issues with error-prone environments. 2. Unrealistic assumptions about data distribution. dependency on proximity and direction.	Edelkamp and Schrödl, Guo et al, Worrall et al, Agamennoni et al, Liu et al, Wu, J. et al.

Table 1 continued

Algorithm Category	**Pros**	**Cons**	**Authors**
Incremental Track Insertion	1. Simple and practical algorithm 2. Effective use of KDE methods 3. Addressing challenges posed by noisy and low sampling rate trajectories.	1. Omitted steps for complexity guarantee 2. Dependency on threshold values for skeleton construction.	Ahmed and Wenk, Biagioni and Eriksson, Cao and Krumm, Karagiorgou, S., Pfoser, D., Skoutas, D.
Intersection Linking	1. Detection and linking of intersections 2. Providing a cost-effective alternative to expensive road surveys for generating road maps.	1. Working best for well-aligned maps 2. Requiring frequent data sampling	Karagiorgou and Pfoser, Alireza Fathi, John Krumm.

Table 1 continued

Algorithm Category	**Pros**	**Cons**	**Authors**
Other	1. Efficient handling of low-frequency and unstable trajectory data 2. Increased accuracy and connectivity of extracted road intersections	1. Limited discussion on generalizability to different areas or road networks 2. Challenges in extracting road centerlines from sparse trajectories.	Deng, M., et al, Li, L., et al.

Having established the foundation of the literature review and introduced our innovative approach, the next section will delve into the data description. By providing an in-depth overview of the data used in this study, including its collection process, key attributes, and relevant characteristics, we aim to provide a comprehensive understanding of the dataset and its suitability for our proposed method.

CHAPTER 3. DATA DESCRIPTION

For this research, a one-month subset of the Wejo connected vehicle dataset was utilized to extract road infrastructure information from vehicle trajectories in the Ames, Iowa Story county area (Figure 1. Map of Iowa state with county borders (Story County with borders in red color). Wejo is a leading connected car data company that collects and provides real-time and historical data from a diverse range of vehicles, including GPS location, speed, acceleration, and other relevant attributes. The dataset used in this study comprises anonymized and aggregated vehicle trajectory data collected over a specific period.

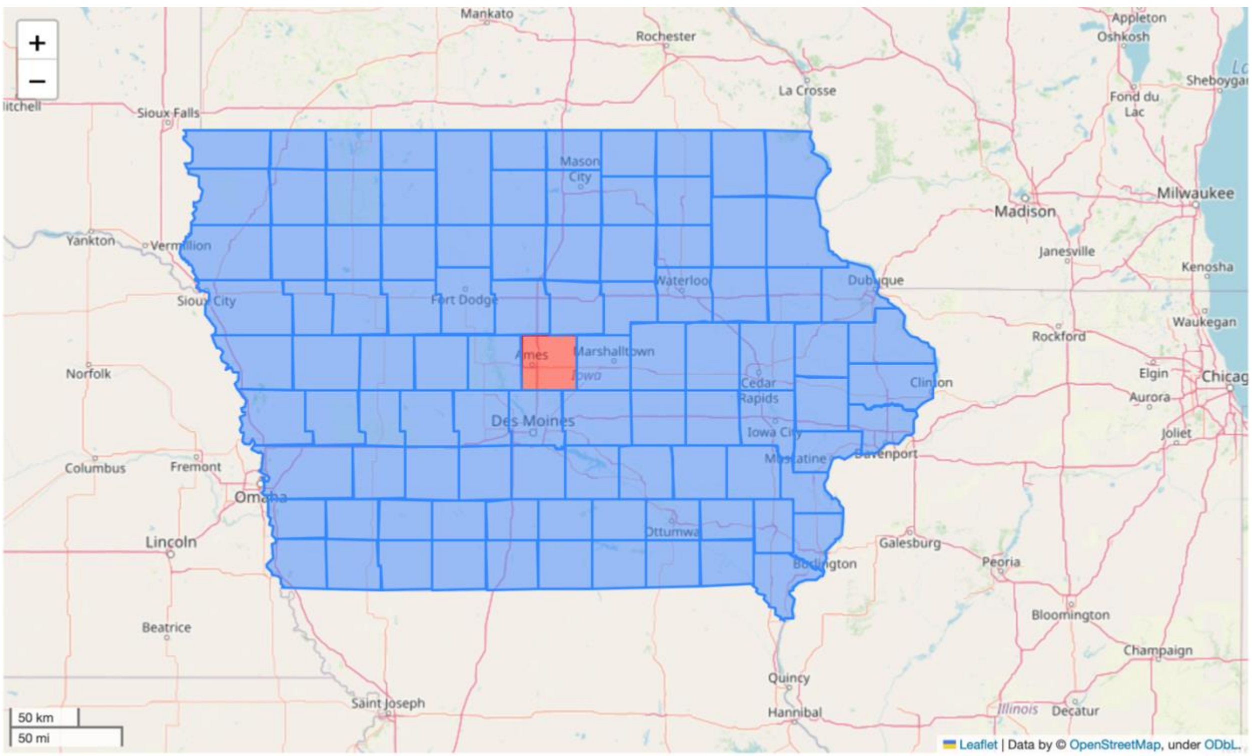

Figure 1. Map of Iowa state with county borders (Story County with borders in red color)

Data Source

The Wejo connected vehicle data used in this research was obtained from dataset repository of the Institute for Transportation (Iowa). The dataset covers a wide range of geographical locations and contains information from various vehicle types, including passenger cars, trucks, and buses. The dataset offers a rich source of information for studying road network characteristics and extracting valuable insights for road infrastructure analysis.

Geographical Scope

The focus of this study is on the road infrastructure of the Ames, Iowa area as shown in Figure 2. Geographical area of Ames. The Ames area was chosen due to its diverse road network, encompassing urban, suburban, and rural environments, which allows for a comprehensive analysis of road infrastructure (Figure 3. Specific roadways used in Ames area) extraction techniques. Additionally, Ames serves as an excellent representative location for exploring the applicability and effectiveness of geohashing and image classification methodologies.

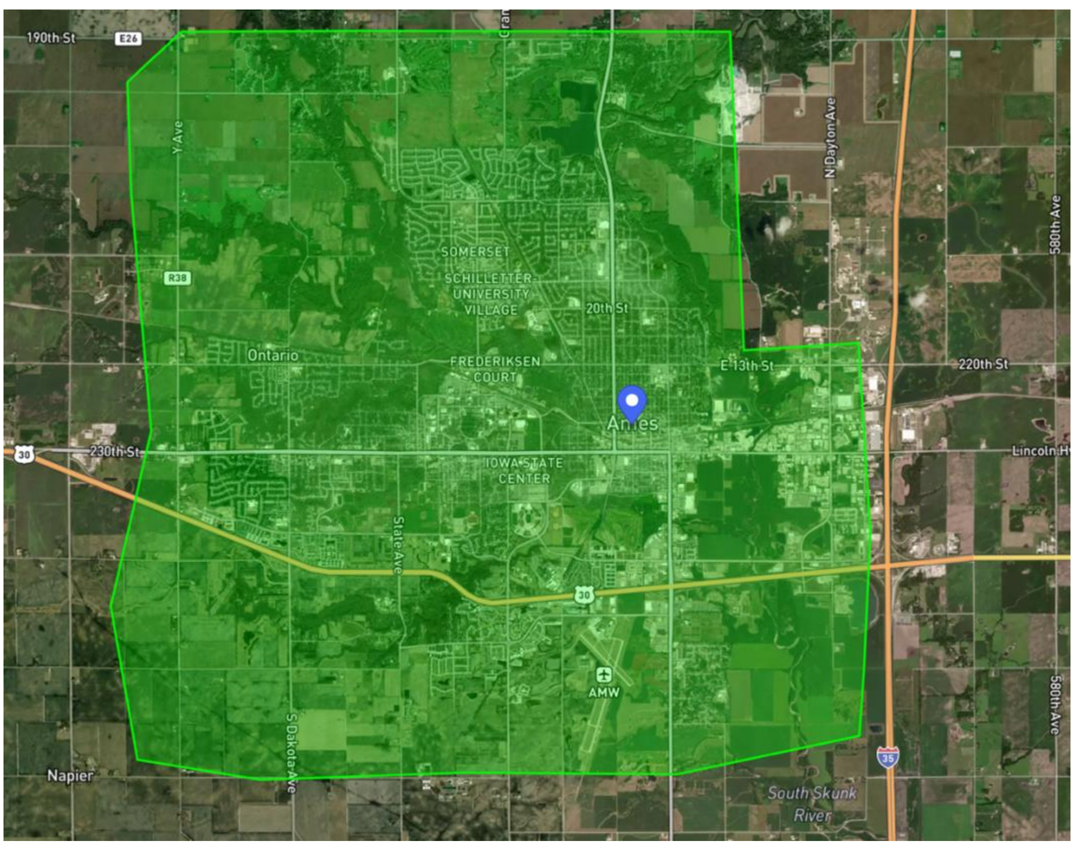

Figure 2. Geographical area of Ames

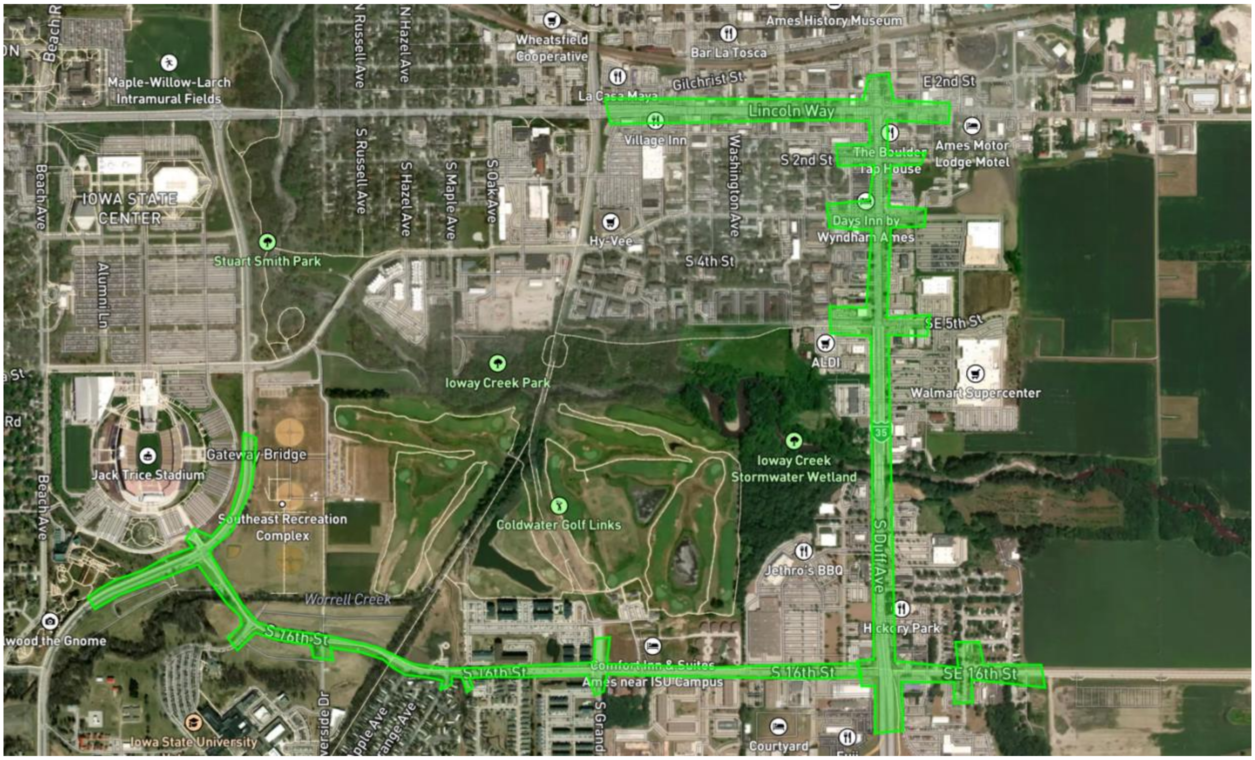

Figure 3. Specific roadways used in Ames area

Data Exploration

In the Data Exploration phase, an analysis of the dataset revealed interesting insights regarding the number of unique vehicle journeys recorded on each day as shown in Figure 4. Number of journeys per day .The journeyid counts provide valuable information about the activity level within the dataset over time.

The analysis shows that the highest number of unique vehicle journeys occurred on the 4th day, with an impressive count of approximately 5800 journeys. This peak activity suggests a significant amount of vehicular movement and usage of the road network on that day, indicating potential areas of high traffic or increased transportation demand.

Conversely, on the 13th day, the journeyid count dropped to zero. This absence of records is attributed to the unavailability of data for that specific day. It is important to acknowledge such instances of missing data as they can impact the overall analysis and interpretation of the dataset.

These findings highlight the variability in the number of unique vehicle journeys captured by the dataset over time. The observed patterns reflect fluctuations in the level of vehicular activity, which can be influenced by various factors such as weekdays, weekends, holidays, or specific events.

Understanding the distribution of journeyid counts and identifying the highest and lowest counts contributes to a comprehensive analysis of the dataset. This information can be further explored to study the characteristics and trends associated with different levels of vehicular activity, providing valuable insights for road infrastructure analysis and planning.

Overall, the journeyid counts on different days showcase the dynamic nature of the dataset, demonstrating the varying levels of vehicular movement and emphasizing the importance of considering temporal aspects when analyzing the data.

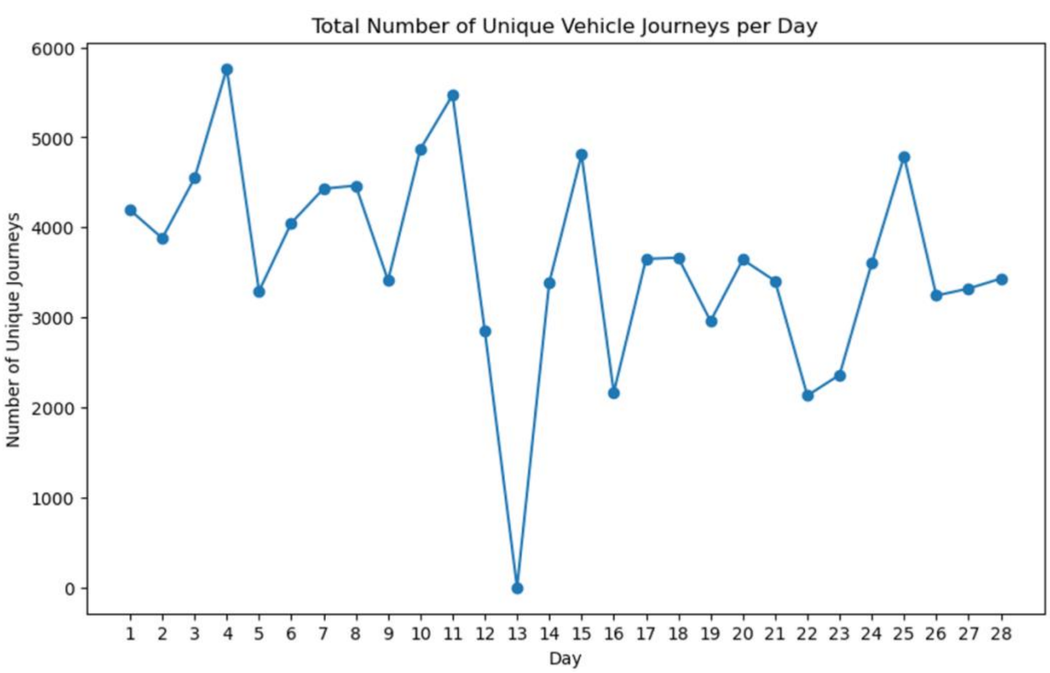

Figure 4. Number of journeys per day

Limitations

It is important to note that the Wejo connected vehicle dataset, while extensive, may have certain limitations that could impact the generalizability of the results. These limitations include potential biases in the vehicle sample, varying data quality across vehicles, and the absence of certain road network attributes. However, efforts were made to mitigate these limitations through rigorous preprocessing and validation procedures, as well as by focusing on a specific geographical area to ensure consistency in the data analysis.

CHAPTER 4. METHODOLOGY

The methodology section of this thesis aims to provide a detailed account of the process employed to extract road infrastructure information from connected vehicle trajectory data using geohashing and image classification with YOLOv5. Building upon the data description outlined previously, which includes details about the origin, characteristics, and data exploratory of the connected vehicle trajectory data, the proposed methodology proceeds with the implementation of geohashing techniques to partition the trajectories onto a plot. This partitioning generates image representations of road segments. Subsequently, these images undergo processing with YOLOv5, a cutting-edge object detection algorithm, to classify and identify straight roads and intersections. The section will elucidate the step-by-step procedure followed, including data preprocessing, geohashing implementation, image generation, YOLOv5 configuration, and model training. Thorough explanations and justifications will be provided to validate the effectiveness and accuracy of the proposed approach. The ultimate objective of this research is to enhance road network analysis, traffic management, and autonomous vehicle navigation systems through the utilization of this innovative methodology.

Data Preprocessing

In data processing, the initial step involves removing null vehicle coordinates to ensure the integrity and accuracy of the dataset. Null coordinates can arise due to various reasons such as GPS signal loss or data transmission errors. By eliminating these null values, we aim to ensure the reliability of the subsequent analysis.

Following the removal of null coordinates, the next crucial step is to convert the vehicle data, which is initially provided as geographic coordinates, into line trajectories. This conversion

(Figure 5. Conversion of coordinates to line trajectories) is necessary to represent the vehicle movements as continuous paths. To achieve this, the coordinates belonging to each unique vehicle journey ID are joined by a line, effectively connecting the consecutive points, and forming a coherent trajectory. This conversion from individual coordinates to line trajectories enables a more comprehensive representation of the vehicles' movements, facilitating subsequent analysis and visualization of the road infrastructure.

Figure 5. Conversion of coordinates to line trajectories

Geohashing implementation

The next subject focuses on the implementation of geohashing techniques, which play a crucial role in the extraction of road infrastructure information from vehicle trajectories. Geohashing is a method used to encode geographic coordinates into a string of characters, allowing for efficient spatial indexing and retrieval of data. It provides a systematic way to divide the Earth's surface into grids of various sizes, enabling spatial operations and analysis at different levels of precision (Figure 6. The 6g cell and its sub-grid).

The concept of geohashing was first introduced by Gustavo Niemeyer in 2008 as a way to create short, unique, and location-based URLs. Inspired by the ideas of David Troy and Marius Eriksen, Niemeyer developed the geohashing algorithm and proposed its application for spatial indexing and data retrieval. The algorithm gained popularity within the geospatial community and has since been adopted in various fields, including data analysis, mapping, and geolocation services. Geohashing owes its effectiveness to the works of Michael O. Rabin, who introduced the concept of space-filling curves, and Édouard Lucas, who pioneered the use of number theory in mathematical algorithms. These contributions paved the way for the development of geohashing techniques and their subsequent implementations in geospatial analysis. Today, geohashing continues to evolve as researchers and practitioners explore new applications and advancements in spatial indexing and data representation.

Figure 6. The 6g cell and its sub-grid

Geohashing employs a hierarchical structure where each level of precision corresponds to a different grid size as shown in Table 2. Metric dimensions for geohash string lengths. Geohash ranges from 1 to 12 levels, at lower levels, the grid cells cover larger areas, providing a more generalized representation, while higher levels offer finer granularity by dividing the surface into smaller cells. The choice of geohash precision depends on the specific requirements of the analysis, striking a balance between accuracy and computational efficiency. For the implementation of geohashing techniques in this study, a precision level of 8 was employed to generate geohash codes for each vehicle coordinate. By selecting a precision level of 8, the geohash codes achieve a balance between spatial accuracy and computational efficiency.

Table 2. Metric dimensions for geohash string lengths.

Geohash Precision Levels	**Grid Area (width X height)**
1	5,009.4km x 4,992.6km
2	1,252.3km x 624.1km
3	156.5km x 156km
4	39.1km x 19.5km
5	4.9km x 4.9km
6	1.2km x 609.4m
7	152.9m x 152.4m
8	38.2m x 19m
9	4.8m x 4.8m
10	1.2m x 59.5cm
11	14.9cm x 14.9cm
12	3.7cm x 1.9cm

Once the geohash codes are generated, the unique geohash codes are utilized to generate bounding boxes (Figure 7. Bounding boxes from geohash boxes). These bounding boxes serve as spatial containers that encompass the corresponding trajectory segments (Figure 8. Geohash boxes overlaying vehicle). By defining the boundaries of each geohash cell, the bounding boxes enable the subsequent clipping of trajectories, isolating specific road segments for further analysis.

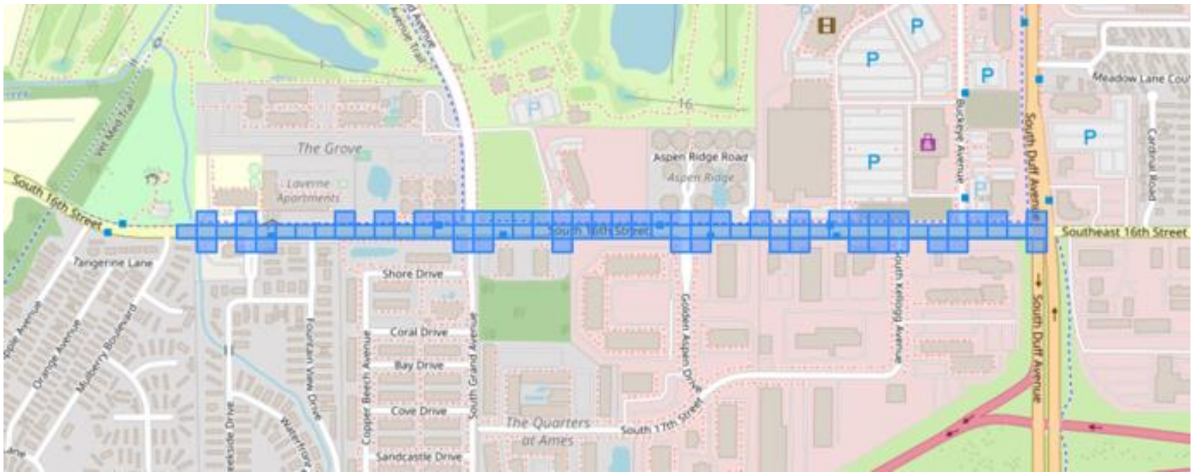

Figure 7. Bounding boxes from geohash boxes

Figure 8. Geohash boxes overlaying vehicle trajectories.

The utilization of geohash codes and the generation of bounding boxes allow for the efficient organization and partitioning of the trajectory data. This approach simplifies the subsequent steps in the methodology, as it provides a structured representation of the road network, allowing for targeted analysis and processing of specific road segments.

This geohash drawing on the trajectories serves as a foundational step for subsequent image generation and road segment classification.

Image generation

The next sub-section of the methodology section focuses on the generation of images using the geohash boxes. To generate these images, the geohash boxes are employed as a means of partitioning the trajectories and extracting relevant road segments (Figure 9. Clipping trajectories for images). By utilizing the bounding boxes (Figure 8. Geohash boxes overlaying vehicle) associated with each unique geohash code, the trajectories are clipped within their respective spatial boundaries.

Once the trajectories are clipped, they are plotted on a plot figure. This plot figure (Figure 10. Plotted vehicle trajectories.) serve as a visual representation of the road segments contained within each geohash box. By plotting the trajectories, the inherent spatial information and characteristics of the road infrastructure are preserved.

After plotting the trajectories on the plot figure, it is saved as an image file. This image file becomes the input for the subsequent classification model based on YOLOv5. The saved images capture the extracted road segments, providing a standardized format that can be easily processed and analyzed by the object detection algorithm.

The generation of images using the geohash boxes facilitates the integration of spatial information into the image-based classification approach. By partitioning the trajectories and creating visual representations, this methodology ensures that the subsequent classification model can effectively identify and classify road segments within the images, contributing to the overall objective of extracting road infrastructure information from the vehicle trajectories.

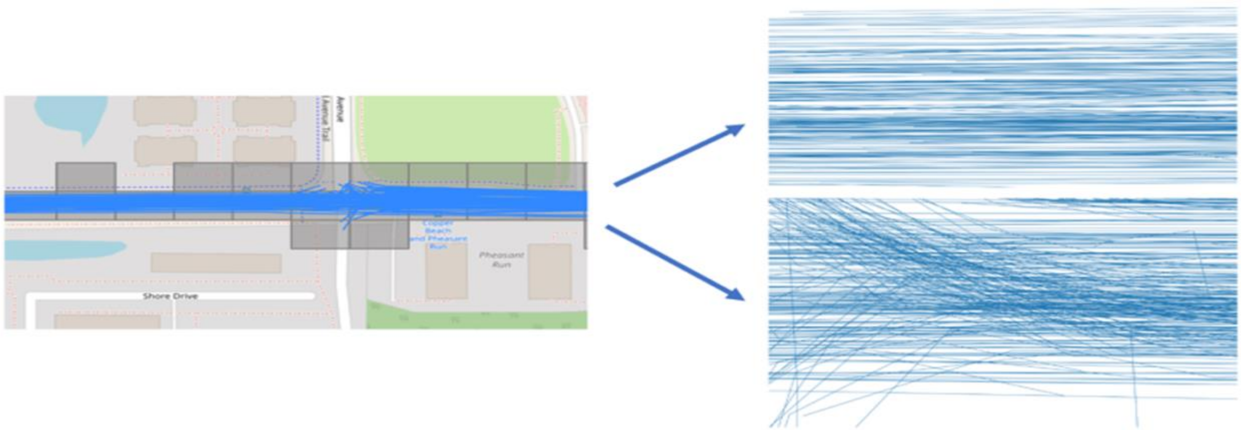

Figure 9. Clipping trajectories for images

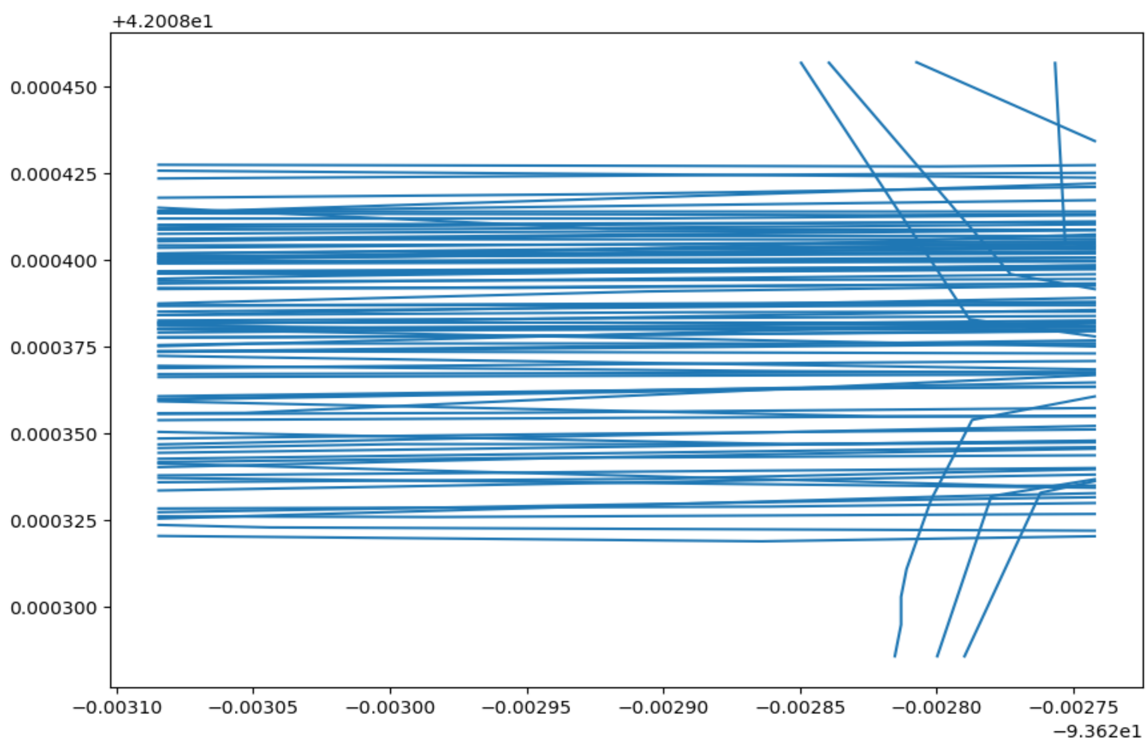

Figure 10. Plotted vehicle trajectories.

YOLOv5 Configuration

Building upon the image generation process from the previous subtopic, the subsequent step in the methodology involves classification using the YOLOv5 model. YOLO, an acronym for "You Only Look Once," is a highly popular object detection algorithm known for its speed and accuracy. It operates by dividing images into a grid system, with each cell in the grid responsible for detecting objects within itself. This unique approach sets YOLO apart from other object detection algorithms.

The YOLO algorithm divides an image into N grids, where each grid has a fixed size of SxS dimensions. Each of these grids is tasked with detecting and locating the objects contained within them. For each grid, YOLO predicts B bounding box coordinates relative to the cell's coordinates, along with the corresponding object label and the probability of the object being present in that cell.

While this approach reduces computational complexity by handling both detection and recognition within each grid cell, it can result in duplicate predictions. Since multiple cells might predict the same object with different bounding box coordinates, YOLO addresses this issue using a technique called Non-Maximal Suppression.

Non-Maximal Suppression enables YOLO to suppress redundant bounding boxes. The algorithm starts by examining the probability scores associated with each prediction and selects the one with the highest score. Then, it suppresses the bounding boxes that have the largest Intersection over Union (IoU) with the chosen high-probability bounding box. This process is repeated until the final set of bounding boxes is obtained, effectively removing duplicates, and ensuring accurate object localization.

As YOLO progresses through training epochs, it refines its predictions, resulting in improved and less noisy object detections. The algorithm's ability to perform object detection quickly and accurately has made it widely adopted and celebrated in various computer vision applications.

The figure below (Figure 11. YOLO bounding box refinement across epochs (source: original paper of YOLO V1).) illustrates how YOLO generates multiple bounding boxes during the initial epochs and gradually refines its predictions, resulting in more precise and less noisy object detections.

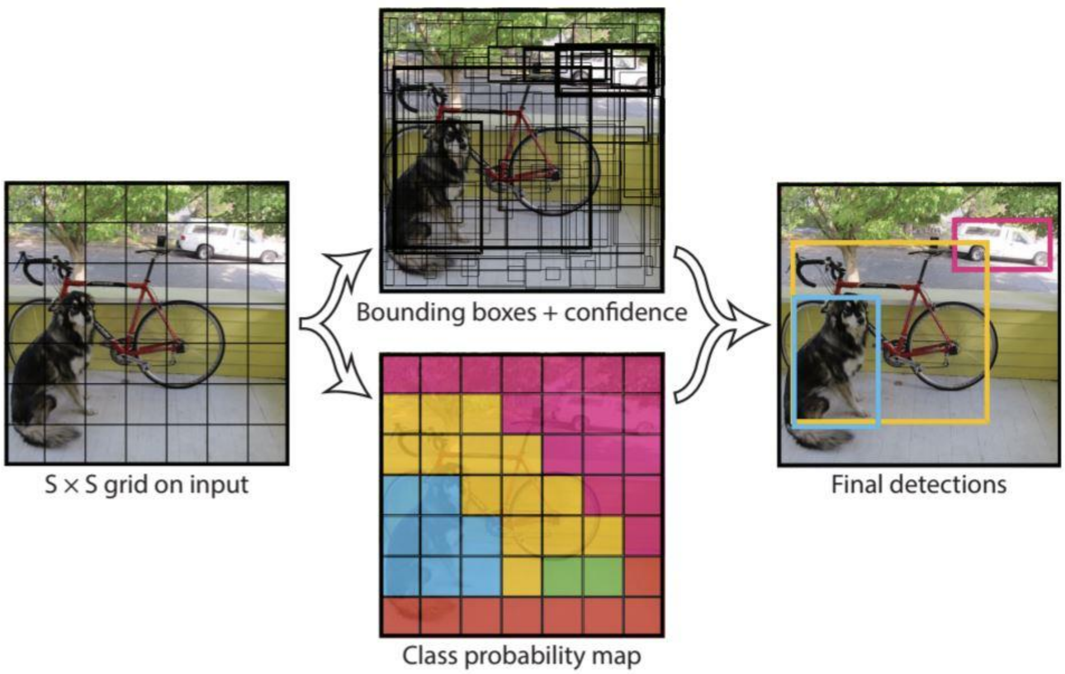

Figure 11. YOLO bounding box refinement across epochs (source: original paper of YOLO V1).

By leveraging its unique grid-based approach and employing Non-Maximal Suppression to handle duplicate predictions, YOLO achieves remarkable speed and accuracy in object detection tasks. Its efficiency and effectiveness make it a powerful tool in road infrastructure extraction, facilitating road network analysis, traffic management, and enabling advancements in autonomous vehicle navigation systems.

YOLO Architecture

The YOLO architecture is a deep neural network designed for object detection tasks. It consists of multiple layers that collectively enable the model to detect and classify objects within images.

The YOLO architecture is commonly composed of a series of convolutional layers followed by fully connected layers. These layers form the backbone of the model and are responsible for extracting features from the input image.

To illustrate the YOLO architecture, refer to the following image (Figure 12. YOLO architecture.):

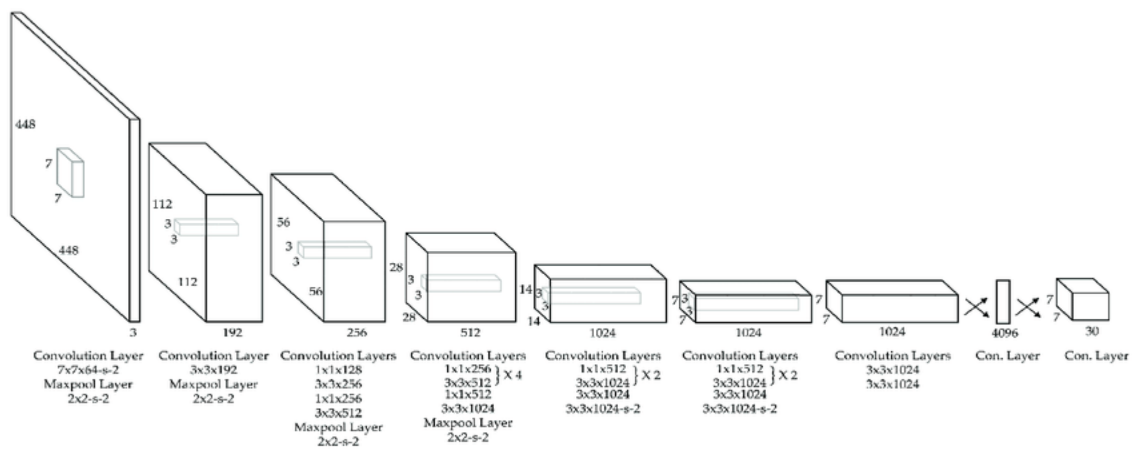

Figure 12. YOLO architecture.

Figure 12. YOLO architecture. showcases the different layers present in the YOLO network. At the beginning of the architecture, the input image is passed through several convolutional layers, typically implemented using the convolutional neural network (CNN) framework, such as Darknet or ResNet.

These convolutional layers perform operations such as feature extraction, feature mapping, and non-linear transformations on the input image. Each layer progressively captures more abstract and higher-level features, allowing the model to learn and represent complex patterns present in the image.

Following the convolutional layers, the YOLO architecture often incorporates a feature pyramid network (FPN). The FPN fuses feature maps from different layers of the backbone network, combining multi-scale information for improved object detection. The FPN enhances the model's ability to detect objects at various sizes and levels of detail within the image.

Beyond the FPN, the YOLO architecture incorporates detection heads, which are responsible for generating predictions. These detection heads typically consist of convolutional layers, which output class probabilities and bounding box coordinates for each grid cell within the image.

In addition to the convolutional layers, fully connected layers are also included in the YOLO architecture. These layers process the extracted features and produce the final predictions, such as the class labels and bounding box coordinates for the detected objects.

Overall, the YOLO architecture is designed to efficiently process images, extract meaningful features, and generate accurate predictions. Its combination of convolutional layers, feature pyramid networks, and detection heads enables the model to detect and classify objects in real-time with impressive accuracy.

Model Training

Model training is a crucial step in developing a YOLOv5 classification model for road infrastructure extraction. It involves training the model using a carefully curated dataset to learn the patterns and features associated with different road segments, such as straight roads and intersections. This subtopic discusses the various preprocessing steps involved, including the test-train split, data preprocessing, and data augmentation. These considerations play a significant role in improving the model's performance and generalization capabilities.

Test-Train Split

The initial dataset consists of 2,217 images, which are categorized into straight roads and intersections. To ensure an unbiased evaluation of the model's performance, a test-train split is performed. The split is as follows:

- Training Set: 70% (1.6k images)
- Validation Set: 20% (445 images)
- Testing Set: 10% (221 images)

This split allows for training the model on a large portion of the data while keeping a separate set for evaluating its performance.

Data Preprocessing

Before feeding the images into the model, preprocessing steps are applied to standardize the data. The following preprocessing techniques are employed:

- Auto-Orient: Ensures consistent orientation of the images.
- Resize: The images are stretched to a fixed size of 640x640 pixels. This resizing step ensures uniformity and compatibility with the model's input requirements.
- Grayscale: Converting the images to grayscale reduces the computational complexity while retaining essential features relevant to road infrastructure extraction (Figure 13. Gray scaled image.).

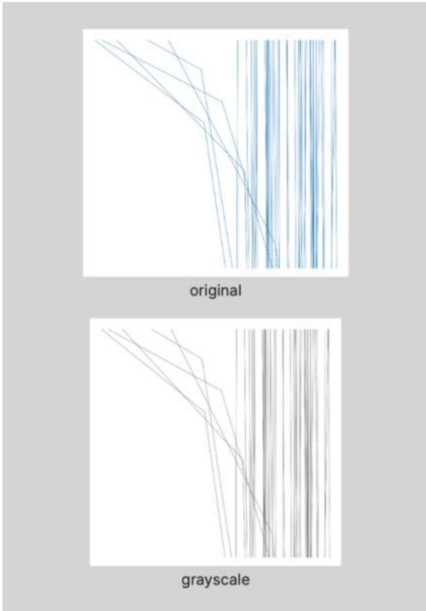

Figure 13. Gray scaled image.

Data Augmentation

Data augmentation is a crucial technique used to increase the diversity and variability of the training data. It helps the model generalize better and become more robust to different scenarios. The following augmentations are applied:

- Flip: Horizontal flipping of images increases the variability and allows the model to learn from flipped instances of the road infrastructure (Figure 14. Flipped image.).

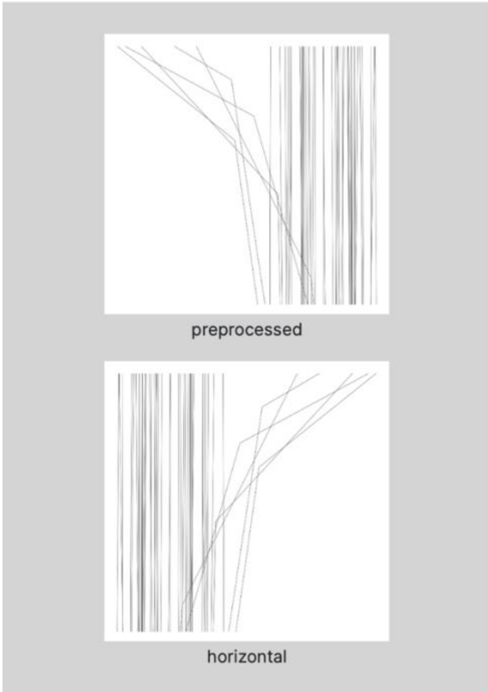

Figure 14. Flipped image.

- Rotation: Random rotation between -15° and +15° introduces variations in the orientation of the road segments, simulating different perspectives (Figure 15. Rotated image.).

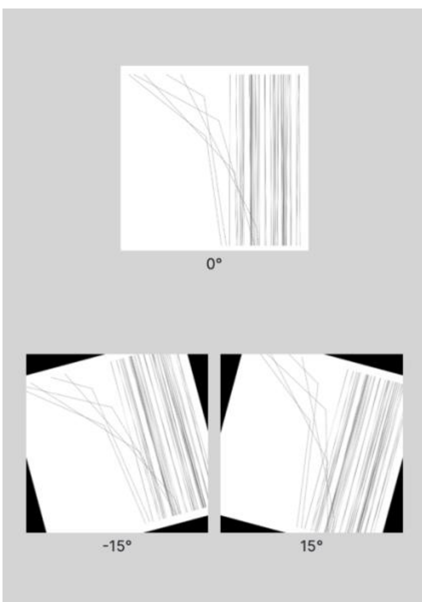

Figure 15. Rotated image.

- Shear: Horizontal and vertical shearing with a maximum angle of ±15° introduces distortions and mimics real-world scenarios (Figure 16. Sheared image.).

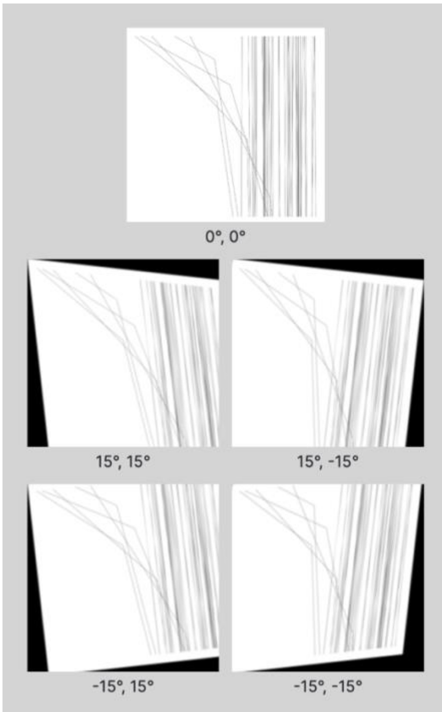

Figure 16. Sheared image.

- Blur: Applying up to 2.5 pixels of blur simulates motion blur or imperfect image quality, enhancing the model's ability to handle such scenarios (Figure 17. Blurred image.).

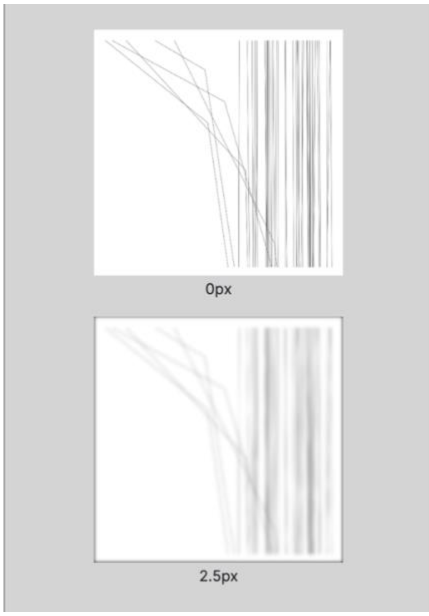

Figure 17. Blurred image.

- Noise: Adding up to 5% pixel noise increases the dataset's diversity and helps the model become more robust to noise in real-world images (Figure 18. Image with noise.).

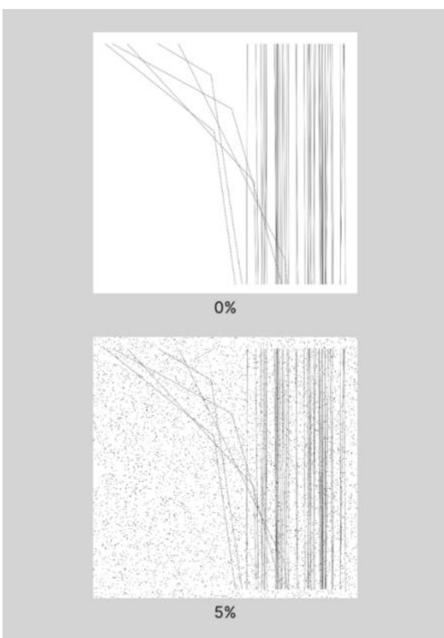

Figure 18. Image with noise.

After applying these augmentations, the dataset expands to 5,900 images. This augmented dataset provides a rich training set with a variety of road infrastructure instances, enabling the model to learn and generalize better.

Through these preprocessing and augmentation techniques, the YOLOv5 classification model is prepared for training. The considerations of test-train split, data preprocessing, and data augmentation collectively contribute to improving the model's accuracy, robustness, and ability to handle real-world road infrastructure extraction scenarios.

In conclusion, the methodology presented in this thesis encompasses a systematic approach to extract road infrastructure information from connected vehicle trajectory data. The combination of geohashing techniques and image classification with YOLOv5 provides a comprehensive framework for analyzing and identifying road segments, including straight roads and intersections. The step-by-step procedure outlined in this section, from data preprocessing to geohashing implementation, image generation, YOLOv5 configuration, and model training, ensures a thorough and effective process for enhancing road network analysis, traffic management, and autonomous vehicle navigation systems. To visualize the overall steps of the methodology, a flow diagram is provided (Figure 19. Flow chart methodology), offering a clear representation of the sequential process. The subsequent section will present the results and discussion, showcasing the effectiveness and accuracy of the proposed methodology in extracting road infrastructure information from connected vehicle trajectory data.

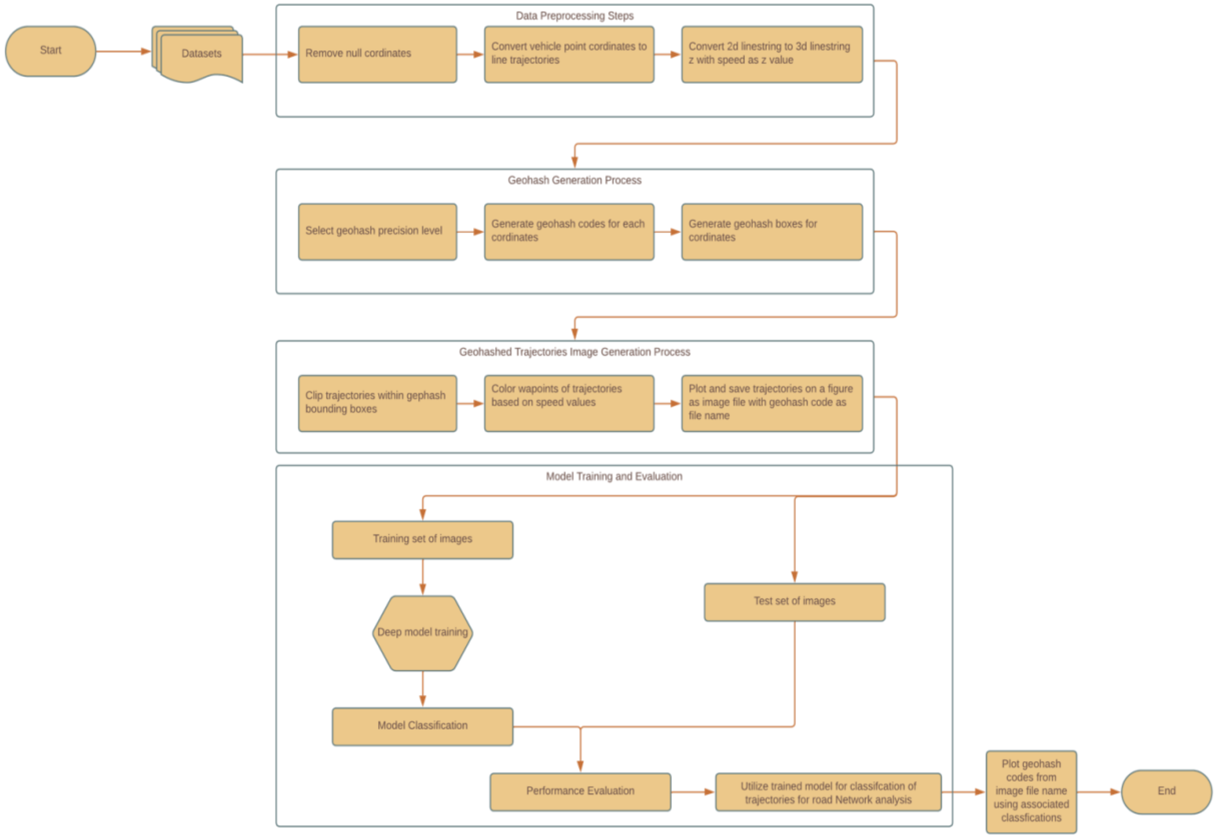

Figure 19. Flow chart methodology

CHAPTER 5. RESULTS AND DISCUSSION

The methodology section has provided a detailed account of the process employed to extract road infrastructure information from connected vehicle trajectory data using geohashing and image classification with YOLOv5. It has outlined the step-by-step procedure, including data preprocessing, geohashing implementation, image generation, YOLOv5 configuration, and model training. With a strong foundation established through these methodological steps, we now turn our attention to the results and discussion of the study. This section aims to present and analyze the outcomes of the implemented methodology, shedding light on the effectiveness, accuracy, and potential implications of the proposed approach. By examining the extracted road infrastructure information and evaluating the performance of the YOLOv5 classification model, we can gain valuable insights into the applicability and advancements of this innovative methodology. Through a comprehensive examination and interpretation of the results, we aim to contribute to the enhancement of road network analysis, traffic management, and autonomous vehicle navigation systems.

The initial results of the trained YOLOv5 classification model, after 100 epochs of training, are presented in Table 3. Performance metrics. This table provides performance metrics for two classes of road infrastructure: "Intersection" and "Straight." The metrics evaluated include precision, recall, F1-score, and support.

Table 3. Performance metrics.

Table Head	**Table Column Head**			
	Precision	***Recall***	***F1-score***	***Support***
Intersection	0.73	0.69	0.71	55

Table 3 Continued

Table Head	**Table Column Head**			
	Precision	***Recall***	***F1-score***	***Support***
Straight	0.90	0.92	0.91	166
Accuracy			0.86	221
Macro Avg	0.82	0.80	0.81	221
Weighted Avg	0.86	0.86	0.86	221

For the "Intersection" class, the model achieved a precision of 0.73, indicating that out of all the predicted instances classified as intersections, 73% were accurate. The recall, which measures the proportion of actual intersections correctly identified by the model, was 0.69. The F1-score, which combines precision and recall into a single metric, was calculated at 0.71. The support column indicates the number of instances present in the dataset for this class, which is 55.

Regarding the "Straight" class, the precision value obtained was 0.90, suggesting a high level of accuracy in identifying straight road segments. The recall for this class was 0.92, indicating that the model successfully detected a significant proportion of the actual straight road segments. The F1-score for the "Straight" class was computed as 0.91. The support column shows that there were 166 instances of straight road segments in the dataset.

To assess the overall performance of the model, the accuracy metric provides an important measure. In this case, the accuracy obtained was 0.86, indicating that the model correctly classified 86% of the road infrastructure instances in the dataset.

Furthermore, the macro average (Macro Avg) and weighted average (Weighted Avg) of the precision, recall, and F1-score across both classes are presented. The macro average provides an equal contribution from each class, while the weighted average considers the support for each class. The macro average precision, recall, and F1-score were calculated as 0.82, 0.80, and 0.81, respectively. The weighted average precision, recall, and F1-score were computed as 0.86, 0.86, and 0.86, respectively.

These initial results demonstrate the promising performance of the YOLOv5 classification model in accurately identifying intersections and straight road segments. The high precision and recall values indicate a balanced trade-off between correctly identifying instances of each class and minimizing false positives and false negatives. The overall accuracy of 0.86 suggests that the model exhibits a strong capability to classify road infrastructure accurately.

Additionally, to evaluate the model's performance on real-world data, we conducted testing using a separate dataset. The confusion matrix below (Figure 20. Confusion matrix for model with uncolored images**Error! Reference source not found.**) provides a comprehensive overview of the model's predictions compared to the actual classes.

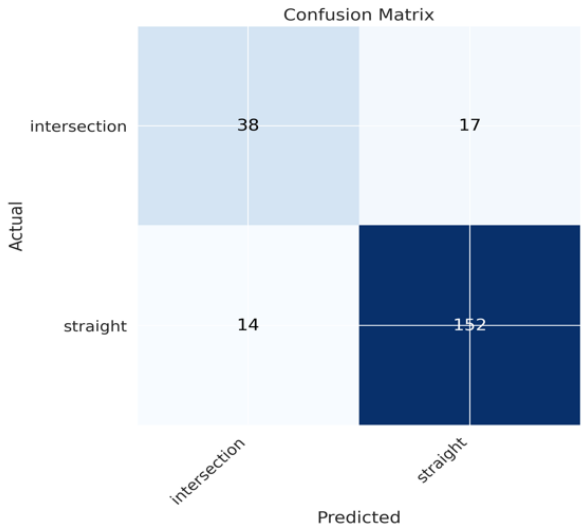

Figure 20. Confusion matrix for model with uncolored images

The confusion matrix reveals the number of instances predicted by the model in each class compared to the actual class labels. In this case, the model correctly classified 38 instances as "Intersection" and 154 instances as "Straight" roads. However, there were 17 instances of "Intersection" incorrectly classified as "Straight," and 14 instances of "Straight" incorrectly classified as "Intersection."

Analyzing the confusion matrix helps us gain deeper insights into the model's performance. It shows that the model is relatively better at identifying "Straight" road segments, with a higher number of true positives (154) and a lower number of false negatives (14). On the other hand, the model struggles slightly in correctly identifying "Intersection" instances, as evident from the lower number of true positives (38) and the higher number of false negatives (17).

Overall, despite some misclassifications, the model exhibits a strong ability to classify road infrastructure accurately, especially in identifying "Straight" road segments. These results further reinforce the effectiveness of the model and its potential applicability in real-world scenarios.

However, in order to improve upon the performance of the model, we conducted further experimentation by retraining the model with a new dataset consisting of images where the trajectories within each geohash were color-coded based on the waypoint speed of each of the vehicle trajectories within that geohash (Figure 21. Sample colored trajectories based on average speed.). This additional information was expected to enhance the model's ability to distinguish between different road infrastructure types based on the average speed of vehicles traversing those areas.

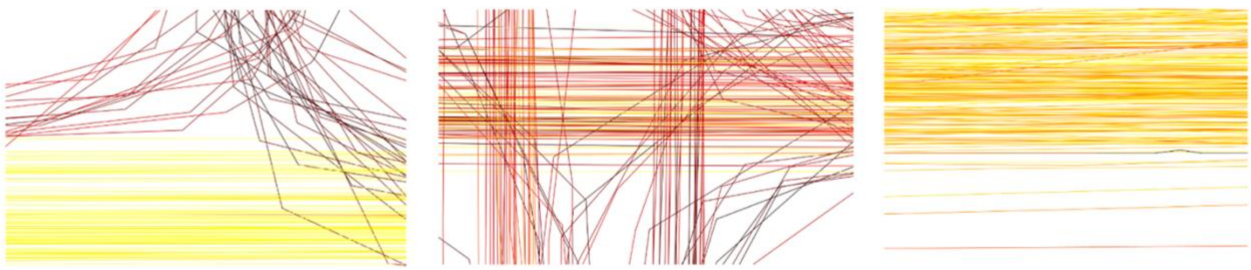

Figure 21. Sample colored trajectories based on average speed.

The performance metrics for the model trained on these new images are presented in Table 4. Performance metrics for colored images. For the "Intersection" class, the model achieved a precision of 0.98, which is significantly higher compared to the previous precision of 0.73 without colored images. This indicates a substantial improvement in correctly identifying intersections. The recall for this class also increased to 0.84, showing that the model detected a greater portion of actual intersections compared to the previous recall of 0.69. The F1-score for intersections was calculated at 0.90, demonstrating a notable improvement from the previous F1-score of 0.71. The support column shows that there were 67 instances of intersections in the dataset.

Table 4. Performance metrics for colored images.

Table Head	**Table Column Head**			
	Precision	***Recall***	***F1-score***	***Support***
Intersection	0.98	0.84	0.90	67
Straight	0.94	0.99	0.97	170
Accuracy			0.95	237
Macro Avg	0.96	0.91	0.93	237
Weighted Avg	0.95	0.95	0.93	237

Regarding the "Straight" class, the precision value increased to 0.94, showcasing a remarkable improvement compared to the previous precision of 0.90 without colored images. This indicates the model's enhanced accuracy in identifying straight road segments when trained on the new dataset. The recall for this class significantly improved to 0.99, surpassing the previous recall of 0.92, and indicating that the model successfully detected nearly all of the actual straight road segments. The F1-score for the "Straight" class was computed as 0.97, which is a notable enhancement compared to the previous F1-score of 0.91. The support column indicates that there were 170 instances of straight road segments in the dataset.

Assessing the overall performance, the accuracy obtained for the model trained on the new dataset was 0.95, a substantial improvement compared to the previous accuracy of 0.86 without colored images. This higher accuracy suggests that the incorporation of average speed information within geohashes has significantly contributed to the model's ability to classify road infrastructure instances accurately.

Comparing the metrics, the precision values for both the "Intersection" and "Straight" classes increased, indicating improved accuracy in classification. The recall values also increased, demonstrating a better ability to detect actual instances of intersections and straight road segments. Similarly, the F1-scores for both classes improved, reflecting a better balance between precision and recall.

These updated results demonstrate the effectiveness of incorporating average speed information within geohashes for improving the model's performance. The significantly higher precision, recall, and F1-scores for both the "Intersection" and "Straight" classes indicate a substantial enhancement in the model's ability to accurately classify road infrastructure instances. The improved accuracy of 0.95 further solidifies the model's capability in correctly identifying road infrastructure types.

These findings highlight the importance of leveraging additional contextual information, such as average speed, to enhance the performance of road infrastructure classification models. However, further analysis and evaluation are necessary to validate the robustness of these results, explore potential limitations, and identify avenues for further improvement.

Additionally, we evaluated the model's performance on real-world data using a confusion matrix. The new confusion matrix is below (Figure 22. Confusion matrix for colored images.Figure 22. Confusion matrix for colored images.).

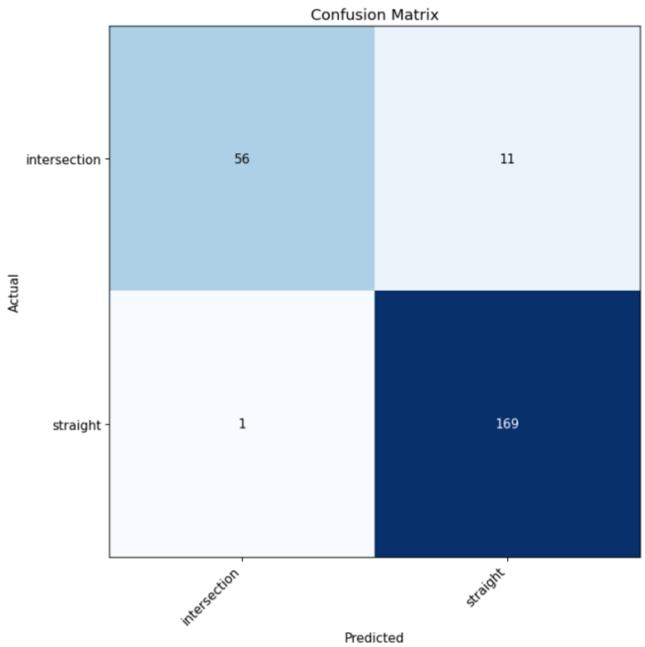

Figure 22. Confusion matrix for colored images.

Comparing this confusion matrix with the previous one, it is evident that the model trained with colored images and average speed information achieves better classification performance. The number of true positives for both classes has increased, with 56 instances of "Intersection" correctly classified and 169 instances of "Straight" correctly classified. The number of false negatives has decreased, indicating a better ability to detect instances of both classes. The overall performance improvement is apparent from the updated confusion matrix.

However, despite the overall improvement in classification performance, there were still instances where the model falsely classified intersection images as straight roads. The images below depict some of these misclassified samples (Figure 23. Falsely classified intersection images.). Upon examination, it becomes evident that several of these images exhibited irregularly shaped trajectories, which posed a challenge for the model in accurately distinguishing them as intersections. Furthermore, some of the images lacked a visible pattern typically associated with intersections, making it difficult for the model to make accurate predictions. Additionally, a few images were not fully captured, further contributing to the misclassification of these instances. These challenging cases highlight the need for further refinement in the model's ability to accurately classify complex road scenarios.

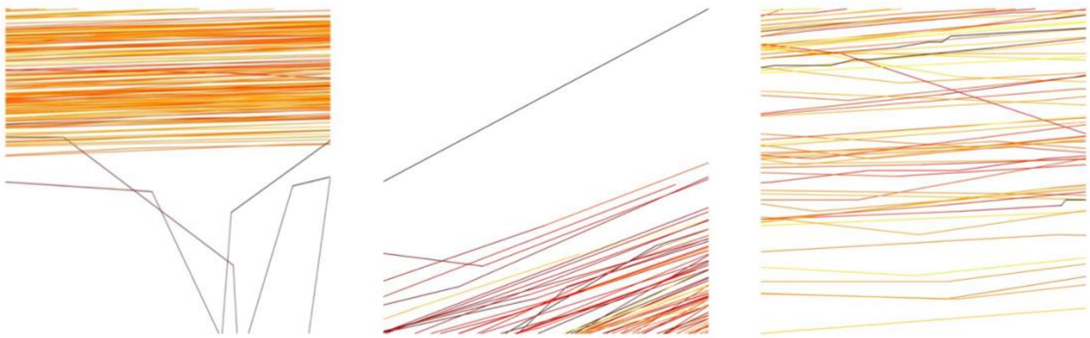

Figure 23. Falsely classified intersection images.

Furthermore, the model also displayed a tendency to falsely classify straight roads as intersections in certain cases as shown in Figure 24. Falsely classified straight road images.. These misclassifications can be attributed to various factors, such as irregularly shaped trajectories observed in some of the images. These irregular trajectories, which deviated from the typical straight path, likely confused the model's classification process. Additionally, the presence of partially captured trajectories within the images further complicated the model's ability to accurately identify straight roads. The model may have struggled to interpret the incomplete information and wrongly associated these instances with intersections due to the lack of a clear and continuous straight trajectory. These challenges emphasize the importance of addressing such complexities to enhance the model's classification accuracy for both straight roads and intersections.

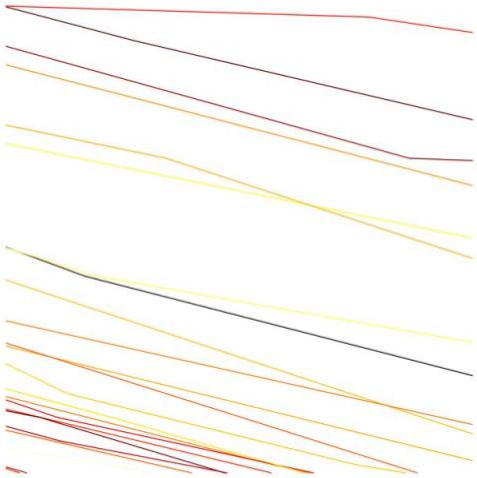

Figure 24. Falsely classified straight road images.

These findings highlight the importance of leveraging additional contextual information, such as average speed, to enhance the performance of road infrastructure classification models. The improved precision, recall, F1-scores, and accuracy achieved by incorporating average speed information within geohashes demonstrate the value of this approach. However, further analysis and evaluation are necessary to validate the robustness of these results, explore potential limitations, and identify avenues for further improvement.

CHAPTER 6. CONCLUSION

In this thesis, we presented a comprehensive approach to road infrastructure classification using the YOLOv5 model from trajectory images generated from geohashes. Our goal was to accurately identify two classes of road segments: "Intersection" and "Straight."

To achieve this, we first trained the YOLOv5 model using a dataset of images representing road segments. After 100 epochs of training, we evaluated the initial performance of the model. The results revealed a reasonable level of accuracy, with precision, recall, and F1-scores of 0.73, 0.69, and 0.71, respectively, for the "Intersection" class, and precision, recall, and F1-scores of 0.90, 0.92, and 0.91, respectively, for the "Straight" class. The overall accuracy achieved was 0.86, indicating a promising start.

However, aiming to further enhance the model's performance, we explored an innovative approach. We retrained the model using a new dataset consisting of images where the trajectories within each geohash were color-coded based on the waypoint speed of each of the vehicle trajectories within that geohash. This additional information was expected to provide a more refined feature representation and improve the model's ability to differentiate between road infrastructure types.

The performance of the model trained on these new images showcased significant improvements. The precision for the "Intersection" class increased to 0.98, while the recall improved to 0.84, and the F1-score reached 0.90. Similarly, for the "Straight" class, the precision increased to 0.94, the recall improved to 0.99, and the F1-score reached 0.97. The overall accuracy achieved by the model trained on the new dataset was 0.95, surpassing the previous accuracy. This demonstrates the effectiveness of incorporating average speed information within geohashes for enhancing the model's classification performance.

Comparing the confusion matrix of the initial results with the one obtained using the model trained on colored images, it is evident that the new approach yielded better classification results. The number of true positives increased, indicating a more accurate identification of road infrastructure instances. The number of false negatives decreased, showcasing an improved ability to detect instances of both classes.

These findings underscore the significance of leveraging additional contextual information, such as average speed, to augment the performance of road infrastructure classification models. The combination of YOLOv5 with colored images based on average speed information within geohashes enabled more accurate and reliable classification of road segments. This research has practical implications for various applications, including traffic management, urban planning, and transportation infrastructure optimization.

However, it is important to note that this study has certain limitations. The evaluation was conducted using a specific dataset, and the generalizability of the model to different datasets and real-world scenarios requires further investigation. Additionally, the proposed approach may have limitations when applied to complex road networks with diverse road infrastructure types and also vehicle trajectories have irregular shapes.

Future research directions include expanding the dataset to encompass a wider range of road infrastructure instances, exploring the model's performance under varying lighting conditions, and considering the incorporation of other relevant contextual features.

Also, future research goals encompass a broader scope of road infrastructure classification, extending beyond the identification of intersections alone. Further advancements in the deep model should focus on detecting different types of intersections, such as signalized and stop intersections, roundabouts, and other complex intersection configurations. This extension will add greater depth to the model's capabilities and enhance its usefulness for comprehensive road network analysis.

Another avenue for future exploration lies in delving into the movements occurring at intersections. Understanding traffic flows, including vehicle turning movements and interactions with pedestrians, will provide valuable insights for traffic management and urban planning. By extending the model's capabilities to capture these intricate interactions, it can aid in optimizing traffic flow, reducing congestion, and improving overall road safety.

In conclusion, this thesis has demonstrated the potential of the deep learning model in accurately classifying road infrastructure instances. By leveraging colored images based on waypoint speed information of vehicle trajectories within geohashes, the model achieved improved precision, recall, F1-scores, and accuracy. These findings contribute to the advancement of road infrastructure classification techniques and pave the way for more sophisticated and effective applications in the field of transportation and urban planning.

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APPENDIX. DATA FORMATS

The dataset used were available in the formats listed in Table 5. Data formats for trajectory data. These include tabular data in plain text form and geo-spatial data formats.

Table 5. Data formats for trajectory data

Data Format	**Description**
CSV	CSV stands for Comma-Separated Values. It is a file format used for storing and exchanging tabular data in plain text form.
Shapefile (SHP)	Shapefile (SHP) is a popular geospatial vector data format developed by Esri (Environmental Systems Research Institute). It is commonly used in Geographic Information System (GIS) software and applications for storing and managing geospatial data
PNG	The PNG (Portable Network Graphics) data format is a widely used lossless image file format.