IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

"Enhancing Uber Taxi Dispatching Efficiency in Urban Areas used CNN and SVM hybrid technique"

Ravi Rathore, OP Kandra,

computer scince,and Engineering

[1]Mtach (CSE)

Sagar Institute of Research and Technology , Indore
Sage University, indore, india

***Abstract*— the system described in the paper focuses on the analysis of an Uber dataset, which captures important information about Uber pickups in a city. The dataset includes key details such as date, time, and geographical coordinates. The primary objective is to leverage the k-means clustering algorithm to categorize distinct areas within the city. This clustering approach is pivotal for enhancing taxi dispatching efficiency, reducing waiting times for both drivers and passengers. The paper acknowledges the rapid growth of the industry and highlights the importance of effective taxi dispatching to meet the increasing demand.To predict demand across various city locations, the system employs machine learning algorithms, including a hybrid model that combines CNN and SVM, as well as the K Nearest Neighbour algorithm. The findings of the experiment demonstrate many performance indicators, including accuracy, precision, recall, and F1-score. These metrics serve as indicators of the effectiveness of the proposed models in predicting and optimizing taxi demand. The integration of machine learning techniques in the Uber dataset analysis demonstrates the potential for improving the overall efficiency and responsiveness of ride-sharing services in urban environments.**

***Keywords*— CNN, SVM, Uber Taxi, Machine Learning ,Deep Leaning ,KNN**

I. Introduction

Data Science and Machine Learning are two interconnected fields that have revolutionized how organizations derive value from data. Data science is the foundation of the data lifecycle, encompassing all stages of data collection, organization, analysis, and interpretation[1]. It aims to identify verifiable information, recurring patterns, and significant trends that inform informed decisions. Machine learning, a subset of AI, develops models and methodologies that enable computers to acquire knowledge from data. Both fields use data to iteratively enhance their performance, with methods such as supervised learning, unsupervised learning, and reinforcement learning. Data science plays a crucial role in informing decision-making processes by providing insights derived from data analysis, while machine learning enhances this process by enabling predictive modeling and automation of decision-making tasks[2]. The synergy between data science and machine learning has led to impactful applications across various industries, such as finance, marketing, healthcare, and more. In finance, predictive modeling can be used for risk assessment and fraud detection, while in marketing; data science informs targeted advertising and optimizes recommendation systems. In healthcare, both disciplines contribute to personalized medicine and disease prediction. However, data science and machine learning face challenges such as data quality issues, ethical concerns, and interpretability of complex models. Ensuring the ethical use of data, addressing biases, and making models explainable are ongoing challenges[3]. The rapidly evolving nature of technology requires continuous learning and adaptation for professionals in these fields. Uber Technologies, for example, provides ride-hailing services and delivery services for food and freight. The Indian government struggled to classify Uber as a technology company or a radio cab service under the "Motor Vehicle Act" in 2019. Uber and Ola are the two largest ride-hailing companies in India, with 13.13 million and 23.96 million monthly active users, respectively. Uber currently holds a 50% market share in India's ride-hailing service, while Ola has 2.5 million drivers. A 2020 study found that 28 million people booked rides with Ola every week, while only 14 million booked rides with Uber. The rise of sharing platforms like Uber and Ola in India is driven by accessibility, efficiency, affordability, and the ability for riders to switch from auto-rickshaws to platform cabs[4]. The rise of sharing platforms can help address infrastructure issues in India, as urban, rich, and educated consumers are more likely to use a sharing platform economy. Uber drivers in India have an average monthly net income of 30,470 INR ($415), while their average monthly cash income is 88,000 INR ($1195). Since 2017, Uber has added a 25% commission to their earnings, causing drivers to react. In June 2018, Uber Lite, an Android app for Android phones, was introduced, linking Uber servers to drivers with poor networks[5]. It also provided access to the Unified Payments Interface (UPI), allowing riders to tip Uber drivers through the app. New drivers undergo orientation at the company's offices, where they learn about the app's features, soft skills, and how the platform works. This shift in gig work in India contrasts with the global North, where gig work takes on new meanings. Uber's service-oriented architecture has evolved since 2014, integrating cabs, food, and freight into a single system. This approach is challenging for Uber to meet demand and fulfill its services, as it relies on GPS technology. The Uber system operates in a live marketplace, facilitating the pairing of passengers with cabs. Uber operates as a technology platform that provides ridesharing and transportation services. It connects riders (demand) with drivers (supply) through its mobile application. The supply service involves on boarding individuals interested in becoming Uber drivers, who must meet certain criteria, such as having a valid driver's license, meeting Uber's standards, and passing a background check. Drivers have the flexibility to choose their own working hours and use the app's navigation system to reach pick-up and drop-off locations. The demand service involves riders requesting a ride, which is displayed on the app, and the algorithm pairs the rider's request with a nearby driver[6]. The rider can track the driver's location in real-time, and the driver can navigate to the pick-up location. Riders and drivers can communicate through the app, and after the trip, riders can rate their experience and provide feedback. Uber employs dynamic pricing, known as surge pricing, determined by the level of supply and demand in a specific geographical location. Payments are cashless and handled through the app, with riders' credit cards or other digital payment methods linked to their Uber accounts. Drivers receive their earnings through the Uber platform. Google's S2 Geometry Library is a spatial indexing system that represents the Earth's surface as a sphere, subdividing the surface into cells of various sizes for efficient indexing and manipulation of spatial data. This library is particularly useful for applications dealing with geographical data and mapping, overcoming challenges associated with traditional two-dimensional mapping systems. Key aspects of the S2 Geometry Library include representation of data on a sphere, spatial indexing, S2 cells, geometric operations, query operations, snap rounding, and mathematical predicates. Google's S2 Geometry Library is a versatile tool that helps Uber efficiently manage real-world geographic datasets. It is released under the Apache 2.0 license, allowing developers to use and modify the library in accordance with open-source principles. The S2 Geometry Library is used for various applications, including geospatial indexing, point-in-region queries, route optimization, geofencing, and dynamic pricing algorithms[7]. Uber relies heavily on geospatial data for ride matching, navigation, and tracking. The S2 Geometry Library provides an efficient way to index and query this data, enabling Uber to organize and access geographic information quickly. Its hierarchical structure facilitates point-in-region queries, helping Uber determine if a given location is within a defined region efficiently. Route optimization is another benefit of S2 Geometry, as it aids Uber in finding the most efficient paths for drivers, reducing travel time, and improving overall service. Geofencing implementations can be enhanced by S2 Geometry, enabling Uber to define and manage these areas effectively[8]. However, challenges and considerations include scalability, accuracy and precision, and integration and maintenance. Scalability is crucial for Uber to maintain system performance, while accuracy and precision may need to be balanced depending on the use case. Uber's software architecture consists of a server service and a frontend service, with Python and SQLAlchemy used to build the object-relational mapping (ORM) layer of the database. The company switched to a "service-oriented architecture" after 2014, allowing the company to bring food and cargo. One of Uber's main challenges is connecting people who need cabs with those who can take them. The design includes a dispatch system, or DISCO, which helps match supply and demand using cell phones[9]. The dispatch system must have goals such as reducing extra driving, minimum waiting time, and overall ETA. Uber's supply service involves taxis, which are monitored using GPS coordinates. Live cabs communicate their location to the server at regular intervals of four seconds, and the precise GPS location is sent to the data center using Rest APIs provided by Kafka. Apache Kafka is used as the data cluster, and the database and dispatch optimizer receive the position, which is comprised of the state machine and the most recent location of the taxis. The demand service monitors where the user is using GPS and meets certain requirements, such as having the right amount of seats, being the right type of car, and not being a pool car. Demand provides the location (cell ID) and the user required to supply and make requests for taxis through the transportation system. The dispatch system matches riders to drivers using DISCO, which divides the map into small cells with unique IDs. Consistent hashing ensures that the work of these cells is spread out among many computers in different places. For example, six different servers control over twelve tiny cells, with two cells given to each server. Supply sends the request to the particular server based on GPS position data. The system generates a circle and eliminates all taxis in the surrounding area that are suited for the rider's requirements. The list of taxis is sent to the ETA to determine the distance between the rider and the cab using the road system rather than geography. The estimated time of arrival (ETA) is sent back to the delivery system for a driver to implement [10]. If Uber is obligated to manage traffic for a newly added city, more servers can be assigned to manage cell IDs for the new city. The scale dispatch system uses Node.js, an event-based and asynchronous web socket, to make the app work well with a lot of riders and handle a lot of traffic. Ring Pop uses the Remote Procedure Call (RPC) standard and a SWIM membership protocol or talk protocol to distribute loads evenly when added or removed. Uber defines a map region with grades A, B, AB, and C, creating subregions within this map region. Uber uses a third-party map service company, Google Maps API, to create maps within their app. Trace coverage is used to identify lost or incorrectly defined road segments, while preferred access (pick-up) point accuracy is determined by the location of the pickup point provided by the Uber application. The estimated time of arrival (ETA) is crucial for matching rides and making money, as it affects the estimated arrival time based on the road system rather than the location. The system uses GPS position data from the driver's app to determine where Uber cars will be every four seconds [11]. Artificial intelligence (AI)-simulated algorithms or the basic Dijkstra algorithm can help determine the best way to move through the data structure. The traits graph displays and models various features, including one-way streets, turn fees, turn restrictions, and speed limits. Uber follows certain rules for databases to provide a better customer experience. These include being able to handle horizontal growth, handling high volumes of read and write operations due to frequent broadcasting of GPS locations by taxis, and maintaining uninterrupted functioning for all functions. To meet these requirements, Uber switched from using PostgreSQL as its Relational Database Management System (RDBMS) database to using various other databases such as NoSQL, Redis, MySQL, Riak, Cassandra, MySQL, and a distributed column store. Analytics is another important aspect of Uber's system. They collect and analyze logs using multiple tools and systems, such as Kafka groups, Hadoop, Elastic search stack, Kibana, and Graphana [12]. They have done various analyses using frameworks and methods such as tracking HTTP APIs, managing profiles, collecting feedback and ratings, promotions and coupons, fraud detection, payment fraud, incentive abuse by drivers, and hacking accounts. In summary, Uber uses a combination of machine learning, machine learning, and various databases to improve its system, lower costs, and user experience. By analyzing logs, tracking HTTP APIs, managing profiles, collecting feedback and ratings, detecting fraud, paying fraud, and addressing account hacking, Uber ensures that its services are accessible and efficient for its users. Uber, a ride-sharing company, has a unique business model that focuses on connecting drivers and riders through a mobile app. The company operates as a two-sided marketplace, connecting drivers (service providers) with riders (customers). The mobile app facilitates transactions and communication between these two user groups. Uber's revenue model is primarily based on commissions, taking a percentage of each ride fare from the driver. The company also charges surge pricing during peak demand periods. The network effects of Uber are beneficial, as the attractiveness of the service to passengers increases in tandem with the number of drivers joining the platform. The company has expanded its services to include Uber Eats, a food delivery service, and Uber Freight, a freight transportation service. This diversification helps the company become less dependent on a single service. Technology integration plays a pivotal role in Uber's business model, with the app facilitating seamless interactions between drivers and riders, incorporating features like real-time tracking, cashless transactions, and dynamic pricing. Advanced technologies like GPS, mapping, and data analytics contribute to the platform's efficiency. Uber's success can be attributed to its car-for-hire service, which connects people who need rides with people who can use their own cars. The company can benefit from the way smart phones work, as both the user and the driver use smart phone technology. The Uber app handles everything from the first ride request to the payment process, allowing users to specify where they want to be picked up when they need a ride[13]. The company also uses advanced technologies like GPS, mapping, and data analytics to enhance the platform's efficiency.

II. LITERATURE REVIEW

K. Muthamil Sudar et.al. (2022) [14] By using R programming, we can analyze Uber data to make predictions about ticket prices, optimize travel time, and choose optimal sites using a heat map. We are in the process of developing a website specifically dedicated to UBER DATA. Efficient taxi dispatching would facilitate less time spent by both drivers and passengers in locating one another. The algorithm is used to predict the demand at different sites around the city. In densely populated urban areas, individuals are sometimes disinclined to drive or choose against using their automobiles owing to the availability of other transportation options. The majority of individuals are inclined to use busses, subways, or cabs. The three means of transportation are significant, however they possess distinct characteristics. The primary distinction among these options is in the fare, which refers to the method of payment. Uber is now experiencing widespread popularity. The primary objective of this project is to provide a website that provides Uber data to users, enabling them to conveniently access this information on their mobile devices.

Rishi Srinivas et.al. (2021) [15] the article provides an explanation of the operation of an Uber dataset, which is comprised of data that Uber has created for the city of New York. Uber is considered a peer-to-peer (P2P) platform. The website connects you with drivers who are able to transport you to the location of your choice. For example, the dataset contains main data on Uber pickups, which includes information such as the date and time of the trip, as well as information on longitude and latitude. Through the use of the information, the article provides an explanation of the application of the k-means clustering method to the data set in order to categorize the different areas of New York City. As a result of the fact that the sector is thriving and is anticipated to expand in the near future. An efficient taxi dispatching system will make it easier for both drivers and passengers to find each other and cut down on the amount of time they have to wait. The model is used in order to forecast the demand at various sites around the city.

Philippe Monmousseau et.al. (2020) [16] A number of lofty objectives have been established for air travel, including the enhancement of the travel experience for passengers via the use of door-to-door trip times as a potential measure. A credible assessment of door-to-door journey times is feasible by using newly available Uber data in conjunction with other online databases. This therefore makes it possible to compare the performance of cities in terms of the excellent integration of their airports, as well as to conduct a study of the whole trip on a segment-by-segment basis of each segment. With regard to the travel experience of air passengers, this model may also be used to better assess the areas in which advancements need and can be made.

III. RESEARCH METHODOLOGY

Machine learning (ML) and data science methodologies form the backbone of modern approaches to extracting valuable insights from complex datasets[17]. In data science, the workflow typically begins with data collection, where diverse and often massive datasets are acquired from various sources. Preprocessing follows, involving tasks such as cleaning, handling missing values, and transforming data into a usable format. Feature engineering is another crucial step, where relevant features are selected or created to enhance model performance [18].

Machine learning techniques are seamlessly integrated into the data science methodology to uncover patterns, relationships, and predictive capabilities within the data. Supervised learning algorithms, including regression and classification models, are employed when labeled data is available, enabling the prediction of outcomes or the classification of new instances. Identifying underlying patterns or groups within the data may be accomplished via the use of unsupervised learning methods such as clustering and dimensionality reduction.

The iterative nature of the process involves model training, validation, and testing, where the performance of machine learning models is assessed and refined. Hyper parameter tuning optimizes model parameters for improved accuracy. Ensemble learning methods combine the strengths of multiple models, enhancing predictive power and robustness. Throughout this process, the interpretability of models is carefully considered, ensuring that the insights derived are not only accurate but also understandable and actionable.

In the realm of data science, machine learning is a powerful tool for automating complex tasks, uncovering patterns in large datasets, and making data-driven predictions. The synergy between data science methodologies and machine learning enables organizations to harness the full potential of their data, providing a systematic and efficient approach to solving real-world problems and making informed decisions. As the fields continue to evolve, advancements in machine learning algorithms and data science practices contribute to a deeper understanding of data and its implications across various industries.

AI and ML approaches have been extensively used to address human-centric problems in areas such as smart education, healthcare, cyber security, consumer behavior, and the environment [19]. Consequently, these applications have made significant contributions to the improvement of our society. In the current day, when education is mostly delivered via online teaching, smart classrooms, and virtual blackboard teaching, AI and ML are playing a crucial role in providing high-quality education. AI-powered education offers instructors novel methods to assess their students' performance. An intelligent tutoring system has the capacity to adjust to the learning methods and preferences of the learner, resulting in significant advancements. ML, as a subset of AI, has seen a significant increase in its use within the educational sector.

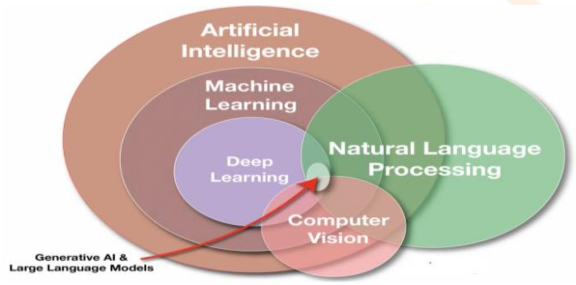

Figure.1: Evolution of AI

IV PROPOSED SYSTEM

The provided code implements a data analysis and machine learning model for predicting Uber pickup locations. The process begins with data selection from a CSV file, followed by data pre-processing, including handling missing values and label encoding. The code then splits the data into training and testing sets, performs exploratory data analysis with histograms and count plots, and creates a hybrid model combining Convolutional Neural Network (CNN) and Support Vector Machine (SVM). The performance of the hybrid model and a K Nearest Neighbour (KNN) model is evaluated, and a comparison graph is generated. Additionally, a prediction interface using Tkinter allows users to input request and driver information for real-time predictions of pickup locations.

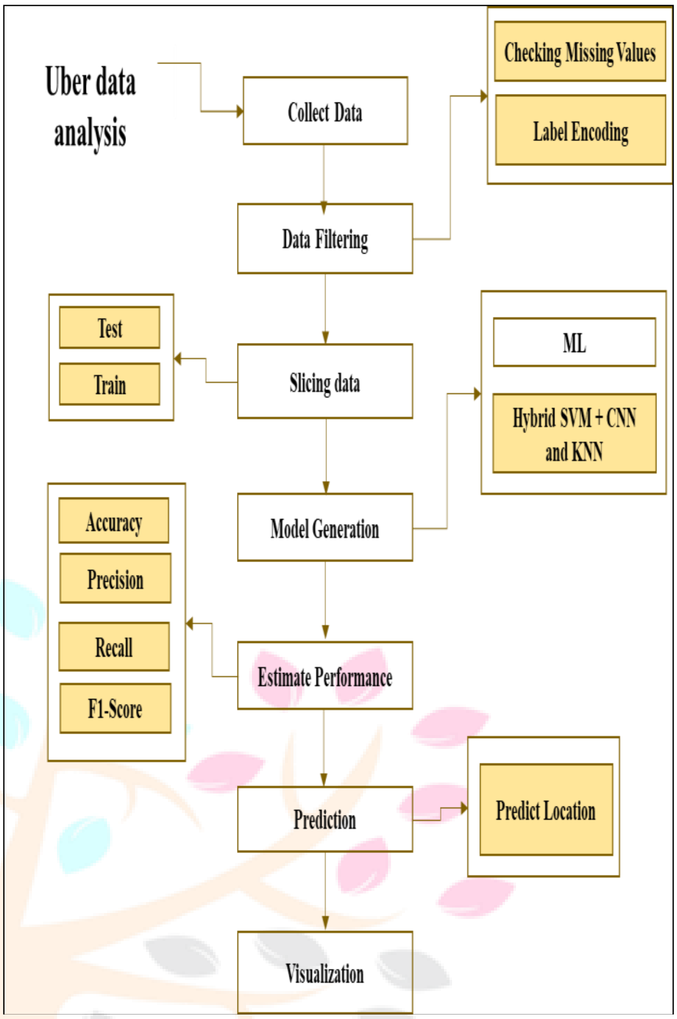

Figure 2: System Architecture

A. Modules:

- Fetch Data
- Data Filtering
- Slicing Data
- Model Generation
- Prediction
- Result Generation

B. Modules Description:

1) *Fetch Data:*

- The input data was collected from dataset repository like kaggle, github and so on.
- Here we can fetch or read or load the collected data by using the pandas packages.
- Our dataset is in the form of '.csv' file extension.
- The dataset contains the information such as pickup location, driver ID , request ID and so on.

2) *Data Filtering:*

- On the other hand, data filtering refers to the act of analyzing a dataset in order to eliminate, reorganize, or distribute data in accordance with certain criteria.

- The dataset is transformed into a structure that is suited for machine learning via the use of pre-processing data transformation techniques.
- In addition, this stage involves cleaning the dataset by deleting any data that is either useless or damaged. This is done in order to improve the correctness of the dataset, which ultimately results in increasing its efficiency.
- Missing data removal
- Normalize the data
- Missing data removal: In this process, the null values such as missing values and Nan values are replaced by 0.
- In addition to removing any missing or duplicate numbers, the data was cleansed of any irregularities that were present.

3) Slicing Data:

- In order for learning to take place throughout the process of machine learning, data are required.
- In addition to the data that are necessary for training, test data are required in order to assess the performance of the algorithm and determine how well it functions before it is implemented.
- For the purpose of our procedure, we regarded seventy percent of the input dataset as the training data, while the remaining thirty percent was regarded as the testing data.
- The process of separating accessible data into two halves, often for the purpose of cross-validation, is referred to as data splitting.
- A portion of the data is used in the process of developing a predictive model, while the remaining portion is utilized to assess the performance of the model.
- One of the most significant aspects of analyzing data mining models is the process of separating the data into groups for training and testing.
- Typically, when a data set is split into a training set and a testing set, the larger portion of the data is allocated for training, while a smaller portion is reserved for testing.

C. Model Generation:

- In our process, we can implement the machine learning algorithm such as KNN and hybrid SVM+CNN.
- In a **1D Convolutional Neural Network (CNN)**, a convolution refers to the process of applying a filter to the input data. The filter, also known as a kernel, is a small matrix that slides over the input data and performs element-wise multiplication with the overlapping portions of the input.
- A **support vector machine (SVM)** is a technique for machine learning that use supervised learning models to handle complicated classification, regression, and outlier identification issues. It does this by conducting optimum data transformations that set boundaries between data points based on predetermined classes, labels, or outputs.
- KNN classifier is an approach for machine learning that is used for solving issues involving classification and regression. After locating the K points in the training dataset that are closest to one another, it then utilizes the class of those points to make a prediction about the class or value of a new data point.

D. Result Generation:

The presented Uber Data Analysis results showcase the system's step-by-step methodology. The initial data selection involves exploring the Uber dataset, displaying sample records, and revealing potential missing values in columns like 'Driver id' and 'Drop timestamp.' The system effectively handles missing data by filling null values with zeros, ensuring a clean dataset for subsequent analysis. Label encoding is applied to transform categorical variables like 'Pickup point' into numerical representations. The data splitting stage involves dividing the dataset into training and testing sets, providing insights into the total number of records and the distribution between training and testing sets. Additionally, graphical representations, such as histograms and count plots, offer a visual understanding of the data distribution. The classification phase introduces the hybrid SVM + CNN model and the K Nearest Neighbor (KNN) algorithm. The model summary for the hybrid SVM + CNN illustrates the neural network architecture. The subsequent training and evaluation of the model provide performance metrics, including accuracy, precision, recall, and F1-score. The KNN algorithm also undergoes training, and its performance metrics are presented.

The prediction component allows users to input values for 'Request ID,' 'Driver ID,' and 'Status' to predict the Pickup Location. The final result indicates the predicted Pickup Location, and performance metrics such as accuracy, precision, recall, and F1-score are discussed. The comprehensive explanation of these performance metrics emphasizes their significance in evaluating the model's predictive capabilities.

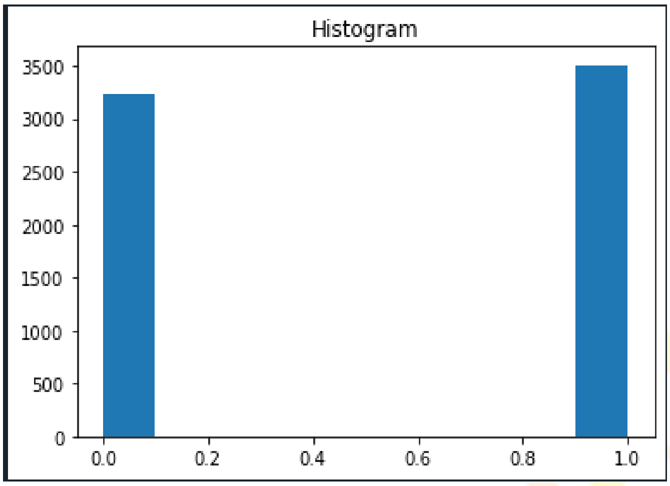

Fig.3: Histogram

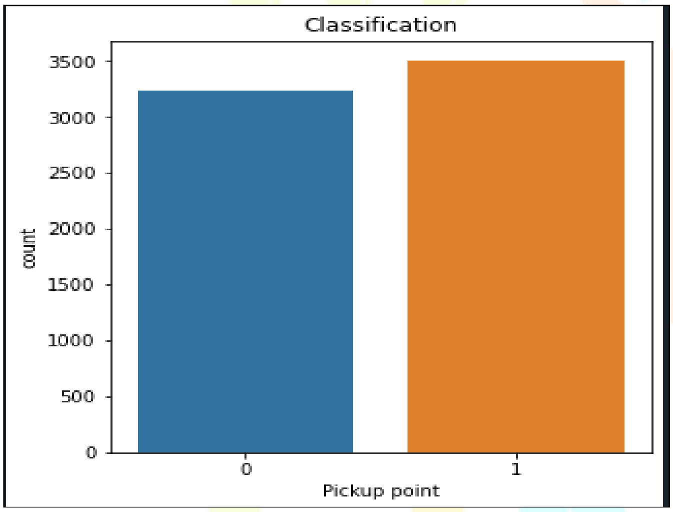

Fig.4: Classification

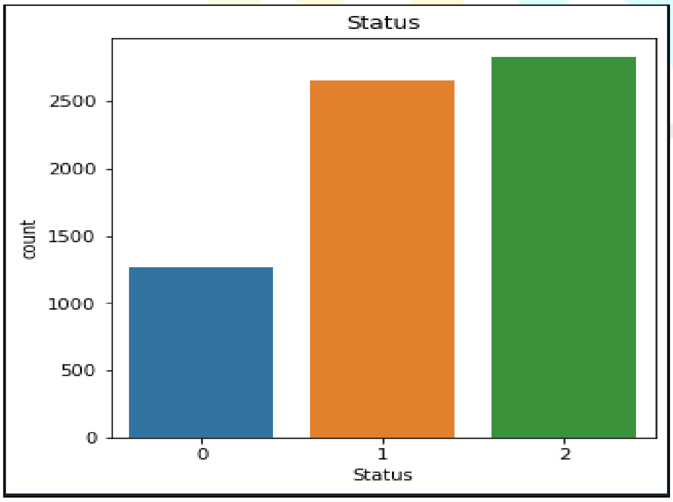

Fig 5: Status

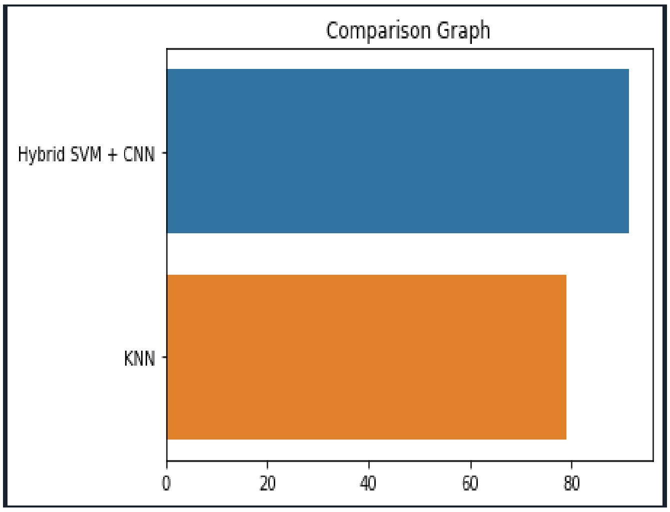

Fig 6: Comparison Graph

E. Performance Metrics

1) **Accuracy:** A classifier's capacity to accurately classify data is referred to as its accuracy. The class label is successfully predicted by it, and the accuracy of the predictor is defined as the degree to which a particular predictor is able to properly estimate the value of the predicted attribute for a fresh set of data.

   AC= (TP+TN)/ (TP+TN+FP+FN)

2) **Precision:** The term "precision" refers to the ratio of the number of true positives to the sum of the number of true positives and the additional number of false positives.

   Precision=TP/ (TP+FP)

3) **Recall:** The level of recall may be calculated by dividing the number of accurate results by the total number of results that should have been collected. The concept of recall is referred to as sensitivity in binary classification.

   Recall=TP/ (TP+FN)

V CONCLUSIONS

In conclusion, this paper presents a comprehensive analysis of an Uber dataset with a focus on improving taxi dispatching efficiency and predicting demand across different city locations. The utilization of the k-means clustering algorithm facilitates the identification of distinct areas within the city, offering valuable insights for optimizing dispatching strategies. The recognition of the industry's rapid growth underscores the importance of leveraging advanced techniques to meet the increasing demand for ride-sharing services.

The introduction of machine learning algorithms, specifically a hybrid model combining CNN and SVM, along with the K Nearest Neighbor (KNN) algorithm, further enhances the system's predictive capabilities. The experimental results, including accuracy, precision, recall, and F1-score metrics, demonstrate the effectiveness of these models in forecasting and optimizing taxi demand. This integration of machine learning techniques into the Uber dataset analysis showcases the impending for significantly improving the overall effectiveness and responsiveness of ride-sharing services in urban environments.

By leveraging advanced analytics and machine learning, the proposed system not only contributes to the optimization of taxi dispatching but also aligns with the evolving landscape of smart transportation systems. The findings presented in this paper provide valuable insights for transportation providers, city planners, and policymakers aiming to enhance the performance and sustainability of urban mobility solutions in the face of growing urbanization and demand for efficient transportation services.

References

[1] 1. Lacy, Sarah (June 15, 2011). "Uber Out-Maths Google on NYC ETAs". TechCrunch. Archived from the original on February 26, 2017.

[2] 2. ^ Rao, Leena (April 18, 2012). "Uber Experiments With Lower-Priced Taxis in Chicago Through Newly Launched Labs Group, 'Garage'". TechCrunch. Archived from the original on January 22, 2018. Retrieved June 25, 2017.

[3] 3. ^ O'Brien, Terrence (April 18, 2012). "Uber tackles Taxis in Chicago with Uber Garage experiment". Engadget. Archived from the original on February 26, 2017. Retrieved February 26, 2017.

[4] 4. ^ Hahn, Fritz (December 4, 2012). "Uber opens doors in D.C." The Washington Post. Archived from the original on February 22, 2017. Retrieved February 20, 2017.

[5] 5. ^ Hartmans, Avery; Leskin, Paige (May 18, 2019). "The history of how Uber went from the most feared startup in the world to its massive IPO". Business Insider.

[6] 6. ^ Thu, Kelsey Brugger (December 19, 2013). "Uber Taxi App a Fit for Santa Barbara?". Santa Barbara Independent. Retrieved March 10, 2020.

[7] 7. ^ Wolff, Michael (December 22, 2013). "Wolff: The tech company of the year is Uber". USA Today. Archived from the original on September 7, 2017. Retrieved September 17, 2017.

[8] 8. ^ Lawler, Ryan (September 2, 2014). "Uber Opens Up UberPool To All San Francisco Users". TechCrunch. Archived from the original on April 23, 2017. Retrieved June 25, 2017.

[9] 9. ^ "Lyft and Uber launch carpool-like services in San Francisco". Los Angeles Times. August 6, 2014. Retrieved March 10, 2020.

[10] 10. ^ Carson, Biz (March 2, 2016). "Uber's GrubHub killer is finally in the US – here's the inside story on its big bet on food". Business Insider. Archived from the original on August 25, 2018. Retrieved September 8, 2018.

[11] 11. ^ Dickey, Megan Rose (January 20, 2016). "Uber's Standalone Food Delivery App Is Coming To The U.S." TechCrunch. Archived from the original on July 7, 2017. Retrieved December 19, 2017.

[12] 12. ^ Crabtree, James (February 9, 2018). "Didi Chuxing took on Uber and won. Now it's taking on the world". Wired. Archived from the original on October 11, 2018. Retrieved October 10, 2018.

[13] 13. ^ Issac, Mike (August 26, 2016). "How Uber Lost More Than $1 Billion in the First Half of 2016". The New York Times. Archived from the original on December 23, 2016. Retrieved February 28, 2017.

[14] 14. K. Muthamil Sudar;P. Nagaraj;V. Muneeswaran;S. Kavya Jeevana Swetha;K. Madhuri Nikhila;R. Venkatesh An Empirical Data Analytics and Visualization for UBER Services: A Data Analysis Based Web Search Engine 2022 International Conference on Computer Communication and Informatics (ICCCI) Year: 2022 | Conference Paper | Publisher: IEEE

[15] 15. Rishi Srinivas;B. Ankayarkanni;R. Sathya Bama Krishna Uber Related Data Analysis using Machine Learning 2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS) Year: 2021 | Conference Paper | Publisher: IEEE

[16] 16. Philippe Monmousseau;Daniel Delahaye;Aude Marzuoli;Eric Feron Door-to-Door Air Travel Time Analysis in the United States using Uber Data 2020 International Conference on Artificial Intelligence and Data Analytics for Air Transportation (AIDA-AT) Year: 2020 | Conference Paper | Publisher: IEEE

[17] 17. ^ Kirby, William (August 2, 2016). "The Real Reason Uber Is Giving Up in China". Harvard Business Review. Archived from the original on January 22, 2019. Retrieved January 22, 2019.

[18] 18. ^ Chappell, Bill (July 31, 2018). "Uber Parks Its Self-Driving Truck Project, Saying It Will Push For Autonomous Cars". NPR. Archived from the original on August 8, 2018.

[19] 19. ^ Hawkins, Andrew J. (June 7, 2022). "Waymo is teaming up with Uber on autonomous trucking because time really heals all wounds". The Verge.