

Car Direction Prediction With The Help of Lidar And AI Technique

Aparna Sharma, M.Tech Scholar, Department of Computer Science & Engineering, Kanpur Institute of Technology, Kanpur, India.
Saumya Awasthi, Assistant Professor, Department of Computer Science & Engineering, Kanpur Institute of Technology, Kanpur, India.

Abstract—**Deep learning and artificial intelligence have led to advances in the performance of the majority of vision-based tasks, bringing them closer to the level of efficiency reached by humans. These advancements have been made possible as a result of recent technological developments. As a further consequence of this development, the probability of there being an autonomous vehicle integrated into the transportation system of the future is increased. The performance at this level was accomplished in large part due to the contributions made by the data obtained from the LIDAR sensor. The value of LIDAR data in the context of autonomous driving is illustrated by the study that has just been presented, which serves as a prime example of its significance. An experimental research into the performance of a vehicle direction prediction using LIDAR data and without using LIDAR data (only image/visual feed is supplied) is the focus of the work that has been presented so far. Examples of deep neural networks include the LIDAR system and the Visual system. Both of these systems are composed of units that are devoted to convolution, as well as long-term and short-term memory, respectively. The architecture of the neural network that is given here took primary inspiration from the I3D network as it was being designed. The experiment shows that the data obtained from the LIDAR has a greater operational efficiency than the data obtained from the visual.**

***Index Terms*—**LiDAR, RFID, Image Processing, Optical sensors, Automatic Vehicle Detection etc.

I. INTRODUCTION

An autonomous vehicle is a vehicle that is able to recognize its surroundings and carry out its operations without the need for any assistance from a human driver. When did it become obligatory for there to always be a living human passenger inside the vehicle at all times? There is never and under any circumstances a requirement that there be a human passenger present in the car at any one moment. An automobile that is capable of driving itself can go everywhere and perform any task that is possible for a conventional vehicle, just like a regular vehicle that is driven by an experienced human driver [1-2].

It is necessary for autonomous vehicles to have sensors, actuators, complex algorithms, intelligent systems, and powerful computers in order for the application to be properly carried out. Autonomous vehicles are able to generate and develop a map of their surroundings based on the data acquired by a number of sensors that are strategically placed throughout the vehicle in a range of locations. These sensors are deliberately placed throughout the vehicle in a variety of areas. Radar sensors monitor the locations of surrounding vehicles as well as their movement. They maintain track of where the vehicles are. In order to keep a watch on the traffic signals, video cameras are employed; the road signs are analyzed; the people operating the other vehicles on the road are followed; and pedestrians are interrogated. Light detection and range sensors, sometimes known as Lidar for short, locate lane markers and road borders by measuring distances using light rays that are reflected off of the car's atmosphere. Lidar is frequently referred to in full as light detection and ranging. In order to facilitate parking, ultrasonic sensors are embedded in the wheels of the vehicle. These sensors can detect obstacles such as curbs and other automobiles. [3].

Figure 1: Autonomous car control display

This complete sensory information is then assessed by the appropriate algorithms, a path is programmed, and instructions for acceleration, braking, and steering power are sent to the vehicle actuators. Because of pre-programmed regulations, obstacle prevention measures, predictive modelling, and object identifiers, computer programmes can more successfully adhere to traffic standards and overcome hurdles.

Vehicles that drive themselves could be a tremendous step forward in terms of preventing and resolving the vast majority of traffic incidents. Currently, studies are being conducted on the sensory apparatus used to guide decision-making and navigational procedures. Although digital image processing (DIP) is a common control system solution in autonomous vehicles, the processing time for DIP necessitates massive equipment requirements as well as extensive logic coding. The driving information processor, or DIP, is designed to ensure that obstacles and other road entities are avoided as much as possible, making a ride in an autonomous car as risk-free as possible [4-6].

Radio Frequency Identification (RFID) is a technology with a wide range of applications, including the retail industry, the medical field, transportation, and the military (Chan, 2010). Autonomous vehicles would be able to detect obstacles on the road and steer clear of them based on their position in relation to the vehicle using radio sonar identification devices. In order to estimate the object's distance and length, radio sonar devices produce radio waves and receive the signals released by those waves as feedback. This would be a more effective method in AVS because vehicles do not need to understand what object is nearby, but simply avoid it. This would ensure that safety concerns are not jeopardised, which is critical.

DIP, unlike radio frequency identification, uses a library of pre-installed identification systems that are based on the object being identified. This method uses up computer resources and causes a slight delay. Because on the road, where items are moving at high speeds, microseconds can equate to scenarios that could mean the difference between life and death, the research will examine a novel way of visualizing AVS systems to present a working hypothesis. Furthermore, by demonstrating the differences in computational processing between the two systems, where RFID appears to be faster than DIP, a new way of envisioning AVS systems will be explored.

Lidar and Radar

The cost of lidar is high, but researchers are still working to discover a method that strikes the ideal balance between distance and resolution. In the event that multiple autonomous vehicles were to ever run along the same course, their lidar signals would greatly interfere with one another, wouldn't they? And if there are a lot of radio frequencies accessible, will the frequency range be enough to allow for the manufacturing of autonomous automobiles in huge quantities?

Weather Conditions

What happens if the weather forecast calls for heavy rain and an autonomous car start driving anyway? In the event that there is a coating of snow along the path, the lane dividers may get obscured [8]. If one road marker is affected by water, sand, salt, or debris, then how can cameras and sensors monitor the other road markings?

Traffic Conditions and Laws

Is it possible for autonomous cars to encounter difficulties in confined spaces like tunnels or on bridges? What are they going to do when they are stuck in such heavy traffic? Is it possible to force autonomous vehicles to stay within a certain lane at all times? They want to use the carpool lane; will they be granted permission to do so?

Benefits of Autonomous Cars

There is no limit to the number of options available to improve one's lifestyle and level of comfort. There would be dignity for those who are physically or intellectually impaired, such as the elderly. If your children were attending a summer camp and they lost their bathing suits or toothbrushes while they were there, they would have those items in their car when they returned home. You should even consider driving your dog to the appointment with the doctor [9-10].

However, the main optimism that comes from autonomous vehicles is that they will be able to significantly cut CO2 emissions. Car automation, renewable energy for automobiles, and car sharing were identified as the three cutting-edge ideas that, if implemented simultaneously, would unleash the full potential of autonomous vehicles in a significant study that was carried out, which was authored by experts. "By 2050, these "three modifications" to public transportation might include the following:

Increase the effectiveness of the traffic flow (30 percent fewer vehicles on the road)

Reduce the cost of transportation by a factor of forty percent (with regards to vehicles, fuel and transportation,)

Encourage walking and cycling, as well as sustainable practices.

Create additional parking spaces that can be used to a variety of other uses (universities, gardens, outlets for communities)

80 percent decrease in the amount of carbon emissions produced by cities around the worlds.

Vehicle communication systems

Individual automobiles can benefit from the information gathered from other surrounding vehicles, particularly information on traffic congestion and safety hazards. Vehicle communication networks use vehicles and roadside units as communicating nodes in a peer-to-peer network, passing information back and forth. As a cooperative solution, vehicular communication systems will help all cooperative cars become more successful. Peer-to-peer networking on the scale required for traffic has yet to be fully implemented: each individual vehicle will have to communicate with hundreds of other cars, some of which will likely go into or out of range. It is critical for autonomous cars to connect with other units in order to operate as efficiently as possible. Multimedia programmes are installed in self-driving cars, allowing users to engage with other self-driving cars and roadway units, among other things, to provide them with accurate information about highway construction and congestion. Furthermore, researchers expect that in the next years, computer algorithms that link and track each autonomous car as it attempts to drive through a barrier will be available. Stoplights and traffic lights must outperform this mode of communication. These capabilities enable automated vehicles in the autonomous vehicle business to recognise and connect with other products and services, allowing them to be improved further (such as intersectional computer systems). This would result in an autonomous network of vehicles that all use the same network and have access to the network's knowledge. The use of other autonomous vehicles will eventually validate the knowledge, resulting in more driverless automobiles using the network. These motions are referred to be network externalities since they will strengthen the feeling of being part of a network.

Reprogrammable

Another feature of autonomous vehicles is that the core product will place a greater emphasis on software and its implications than on the structure and engine. Because the automated systems that drive the car are autonomous, improvements will improve the benefits to the owner by reprogramming or modifying the software (e.g. upgrade to help differentiate blind person versus non-blind person and that when engaging a blind person, the car will take additional due care).

Upgrades must not only come from retailers, as these updates can be programmed and implemented by machine learning, but also from autonomous intelligent vehicles, according to this fully programmable automated vehicle feature (e.g. Primary navigation mapping or new machine intersection systems).

These reprogrammable digital technology elements and the future of smart learning on computers are examples of how autonomous car makers might differentiate themselves in terms of software. This also implies that autonomous vehicles will never be completed because the product must be manufactured on a constant basis.

Digital Traces

Automated vehicles are fitted with sensors and radars of various kinds. As defined, this enables automated cars and/or roadway units of computers to link and communicate with them. This makes sure that when they link or interoperate, autonomous vehicles leave digital traces. In order to enhance the driving capacity or safety of autonomous vehicles, it is possible to use the data from these digital tracks to create updated (to be ascertained) products or to modify them.

Modularity

Traditional vehicles and their associated systems are manufactured as a complete product and, unlike autonomous vehicles, can be improved only if upgraded or repeated. As stated, because of their digital characteristics, autonomous vehicles are manufactured but never done. This is because autonomous vehicles are more flexible because they consist of many parts that can later be explained by a Layered Modular Architecture. By integrating four narrowly connected layers of computers, networks, resources and materials into Automated Vehicles, the Layered Modular Architecture expands architecture of solely physical vehicles.

Light Detection and Ranging (LIDAR)

Light Detection and Ranging, also known as Lidar, is a type of remote sensing system that uses a pulsed laser to convert the shape of light in order to determine distances (varying ranges) from the ground. These light pulses, in addition to the vast majority of other data collected by the aerial system, provide exact information about the surface features of the Universe as well as the origin of the Universe itself in three dimensions.

Figure 2: A high-resolution image of the surroundings is generated by LiDAR system

In particular, a lidar device is made up of a laser, a scanner, and a specialized GPS receiver. All three of these components work together to collect data. Airplanes and helicopters are the types of aircraft that are utilised the most frequently for the processing of lidar data over expansive areas [11]. Bathymetric lidar and topographic lidar are both types of lidar. Green light is also utilised by bathymetric lidar to measure water-penetrating seafloor and riverbed heights. Topographic lidar typically uses a near-infrared laser to scan the soil, while bathymetric lidar often uses green light.

Analyzing both natural and constructed settings in a way that is efficient, accurate, and flexible is made possible by Lidar devices, which are used by mapping experts and scientists. NOAA scientists utilize lidar to render to aid in emergency service operations and in most other uses, digital surface to be used in geographic information in order to build more detailed shoreline maps. These charts may also be used in a variety of other applications.

In 1961, the Hughes Aircraft Company, led by Malcolm Stitch, was responsible for the introduction of the very first device of its kind that was similar to a lidar. This occurred not long after the creation of the laser. This device was attempting to combine laser-guided imagery with the capacity to analyze ranges for satellite tracking in order to use accurate sensors and data acquisition electronics to determine how long it would take for a signal to be restored. In order to do this, the device needed to be able to assess the duration of the signal loss [12]. Coherent Light Detection and Range, Detection and Coherent Light Range, Detector, Radar, Satellite Detection and Range, Radio Detection and Range, Radio Detection and Range, Unity. Coherent Light Detection and Range. Detection and Coherent Light Range. Detector. Radar. Radio Detection and Range. Unity. Early colidar structures are derived not just from laser rangefinders and laser altimeters but also from lidar and laser rangefinder equipment. Colidar Mark II "light In the meantime, "In the meantime," is being used to research the moon. Ultimately, the laser can offer a robust sensitive detector of celestial objects with optical wavelengths. In the meantime, "In the meantime," "is utilised in the process of moon observation (light radar).

The National Center for Atmospheric Science was the first organization to apply lidar technology in the field of meteorology, where it was utilized to monitor clouds and pollution. The accuracy and reliability of lidar systems were brought to the attention of the general public for the first time in 1971, during the Apollo 15 mission, when the astronauts were making use of a laser altimeter to conduct surface measurements on the moon. Even though the term "radar" is no longer regarded as an adjective in American English, and written texts consistently present the term without capitalization, the word "lidar" began to be capitalized as "LIDAR" or "LiDAR" in certain publications beginning in the 1980s. This trend continued until the early 2000s. There is currently no consensus on market capitalization, which suggests that it is unclear if "lidar" should be written in lower case since it is an abbreviation or not, despite the fact that it is an acronym like "radar" and "sonar."

"Depending on the publication, lidar may be referred to as "LIDAR," "LiDAR," "LIDaR," or "Lidar.""

The United States Geological Survey (USGS) commonly uses both "lidar" and "LIDAR" in the same text; the New York Times primarily uses "lidar" for employee-written postings, but Lidar could be used for news feeds like Reuters.

Design

'Incomprehensible' or higher accuracy of energy (which mainly measures represent changes in light intensity) and consistent identification are the two types of lidar detection systems (Best to calculate doppler movements or alterations in reflected light

phase). In general, optical heterodyne detection is used by coherent systems.[23] This is more adaptive than direct detection and enables them to work.
There are pulse models used for both categories: mostly micropulse or highly energetic. Micropulse effectively made use of transient energy spikes. As a consequence of ever-increasing computational power, they have advanced, coupled with laser technology advances. Usually, on the order with one micro-joule, individuals utilize significantly less energy throughout the laser and are therefore "eye-safe" implying they could be used despite safety measures. In scientific research, increased systems are widespread, in which they are commonly used it to determine atmospheric parameter values: cloud height, layering and density, cloud particles (dielectric properties, hyper polarization and light scattering coefficient), pressure, temperature, humidity, wind, and trace gas concentration (nitrous oxide, ozone, methane, etc.)

Components of LIDAR

Lidar systems contains many primary components,

- **Laser**
- **Phased arrays**
- **Micro-electromechanical Machines**
- **Scanner and optics**
- **Photo-detector and receiver electronics**
- **Position and navigation systems**
- **Sensor**

II. Literature Review

A decrease in total travel time as a result of improvements in the effectiveness of traffic management systems would lead to a reduction in total fuel consumption. A reduction in the amount of fuel that is consumed would assist to lessen the impact on the environment that is generated when cars are driven for extended periods of time. Furthermore, with the advent of driverless vehicles operating on the following is a literature review of "Detection of Unmanned Aerial Vehicles via Multi-static Forward Scattering Radar with Airborne Transmit Positions" written by Daniel Gasland, BorgeTorvik, ErlendFinden, Fredrik Gulbrandsen, and RagnerSmestad from the "Norwegian Defence Research Establishment."

Using the LiDAR point cloud, several investigations have been reported out with the goal of monitoring urban land cover and locating structures. The high-resolution surface height intelligence gained from the LiDAR scans was utilised as supplementary data in the form of a digital surface model (DSM), which was afterwards produced from the LiDAR point cloud. (Zhou et al., 2004; Matikainen et al., 2007; Sohn and Dowman, 2007; Lee et al., 2008; Demir and Baltsavias, 2012) or as the major data for categorization (Zhou et al., 2004; Matikainen et al., 2007; Sohn and Dowman, 2007; Lee et al., 2008; Demir and Bal (Ma, 2005; Madhavan et al., 2006; Liu, 2008; Chen et al., 2012). The most recent research makes an effort to characterize the LiDAR point cloud without first translating it into a DSM raster (Rottensteiner, 2003; Sampath and Shan, 2010; Chen et al., 2012). This helps to preserve the inherent geometric qualities of the LiDAR point cloud and, as a result, reduces the amount of error in the classification performance as a whole (Golovinskiy et al., 2009; Zhang et al., 2013).

It is possible to regard the LiDAR points, which lack any obvious spatial structure, as unordered summaries of the measurements. It has been possible to classify LiDAR point clouds using two different methods: pixel-based (point-based) and object-based classification, which are both very similar to raster-based picture classification. In point-based categorization, points are categorized by making use of the few properties that are contained in the point cloud. These qualities include geometry and a particular distance from the surface. The popularity of object-based point cloud evaluation has been on the rise recently due to the fact that it delivers more actionable results. It has been discovered that the abundant spatial and geometric data that is linked with the high resolution LiDAR point cloud can be utilized for the purpose of exact urban scene classification. According to the findings of recent studies, object-based point cloud (OBPC) tagging algorithms are able to exploit the spatial relationships of LiDAR point clouds and produce improved overall performance (Zhang et al., 2013; Golovinskiy et al., 2009).

In 2018, using 3D LiDAR, Behley and Stachniss[32] suggested a new SLAM method, SuMa. A surfer-based map formulation has also been used and the posing mapping function was conquered by using frame and sub-map activation ICP process. The distinction is that within point cloud rendering, the technique utilizes the OpenGL database. Models with different points of view could be accessed in the closed loop identification link, such that the closed loop limitation could be identified and the closed loop can also be strengthened even though there are only limited overlap sections of a point cloud as well as the map; the durability of the detecting link. Hess et al.[33] suggested a branch - and - bound automated system closed-loop predictive algorithm, that also checks for just a point cloud and a sub-score in the position space by getting a simple discrete pose space close to the actual position estimation. For just a higher registration ranking, the map brings the highest pose. The pose quality is being used as the original value whether it continues to exist, as well as the current pose transformation itself is calculated through using procedure of frontend registering and used it as the closed-loop limitation; no closed loop is observed if

something doesn't exist. The scheme is easy and efficient, and is appropriate for the SLAM method's real-time necessity. Even so, the closed-loop detection approach would collapse when another error aggregation crosses the distance threshold.
There are two distinct categories of image segmentation methods: edge-based segmentation and region-based segmentation. Both of these categories are described below. The edge of the probable target is located and identified in order to carry out the edge-based segmentation. The approach begins with the change in the data that was detected as its point of departure. The process of edge detection involves isolating the edge using the gradient as a guide. In addition, some of the more well-known edge detection operators are called Sobel, Canny, Roberts, Prewitt, Kirsch, and Laplacian, among others. The method of image segmentation known as the region-based method separates the pixels in the image into several regions, and the method uses the reliability of the detected data as its point of departure. Methods like the region growing approach, the cluster-based method, and the threshold-based method are all included in region-based segmentation.

In order to carry out the process of segmentation, a large number of the various researches rely solely on the date information obtained from the LiDAR point cloud. Even though, as was stated earlier, it is common knowledge that, depending on the characteristics of its spectral reflectance, multispectral data can differentiate between varieties of materials. This is a well-known fact. Therefore, the combination of geometric properties from LiDAR-based range data and important characteristics from multispectral images might be able to complement one another and provide better performance in the identification and detection of aspects of urban development such as houses, trees and bushes, trees, and trees (Zhang et al., 2013). The classification method (classifier) employed it to mark items plays an extremely important part in the accuracy of the identification of urban objects. This is because the quality of the segmented objects is directly correlated to the accuracy of the identification. According to the findings of our review of the relevant literature, only a single classifier has been applied in studies that make use of the LiDAR point cloud for detecting contemporary buildings (Sun and Salvaggio, 2013; Moussa and El-Sheimy, 2012; Zhang et al., 2013). Because the output of a classifier is specific to the data as well as the location, it has become a recurrent problem to choose which classifier will be most suitable for the task before beginning it. Recent developments in the field of pattern recognition have resulted in the creation of a solution known as the "multiple classifier method" (also known as a "classifier ensemble"), in which a number of different classifiers are applied collectively to the dataset, and the intermediate performances of those classifiers are numerically integrated in order to generate a single output that is superior to either of the individual outputs (Fauvel et al., 2006; Benediktsson et al., 2007; Du et al., 2012; Damodaran and Nidamanuri, 2014). Recent significant breakthroughs in image classification demonstrate the capability of multiple classifier systems for the classification of remote sensing images.

III. METHODOLOGY

Robotics has consistently been a significant focus of research activity in both private industry and academic institutions. The efficiency of human civilization has been improved thanks to a number of robotic devices, which have also made life significantly more convenient for people everywhere. A greater number of academic and conceptual supports, such as mechanical design, electronic design, perception of the surroundings, positioning and mapping, decision-making and control, are required for robotic goods. Simultaneous localization and mapping is one of the many topics that are researched today (SLAM). In all honesty, this is the most effective method for recognizing the autonomous movements of the robot [14]. The SLAM methodology can be summed up as follows: locating a mobile robot in an uncertain area in an unknown place, provided that the robot can construct a map of the external world in stages while evaluating its position based mostly on the map. The SLAM technology recognizes positioning and builds a map by using positioning response, equates the massive environmental information obtained with the map, and adapts the preceding positioning response and the recent map in order to achieve simultaneous positioning and mapping activity. This is accomplished by obtaining information about adjacent scenes. It has been demonstrated that positioning and mapping are two activities that, even with SLAM technology, integrate into one another.

Lidar Model

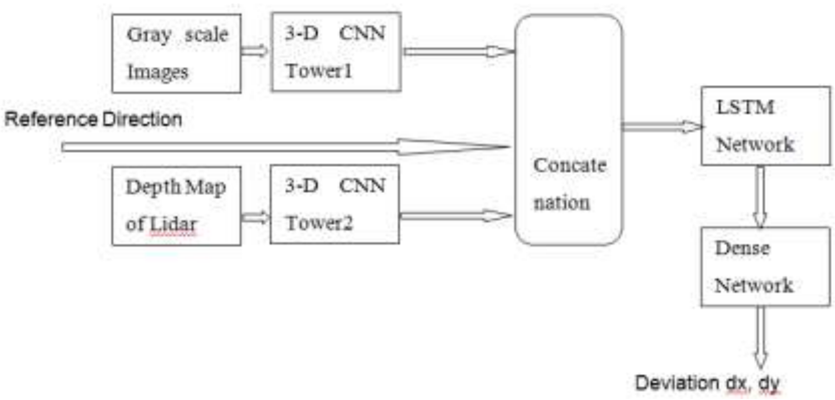

Figure 4: Block Diagram of Lidar Model

The images from the video are first converted into grayscale images and for each image corresponding lidar data (point cloud and intensity map) is converted into depth map images. The sequence of size 32 images and depth maps are created for the training of the model.

The model architecture is inspired by the I3D network. The I3D network is a fixed sequence model but we need a recurrent network so we incorporated a LSTM network before the dense block. The overall architecture of the LIDAR and Image models are shown in figure below.

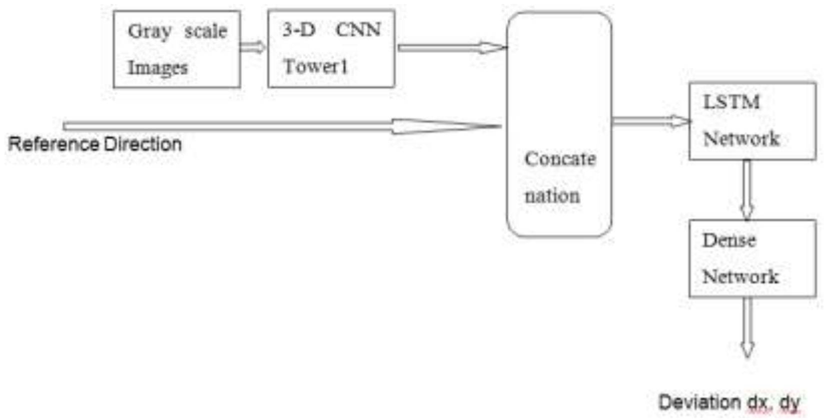

Figure 5: Block Diagram of Image Model

The different components used in the network are separately shown in the figure 3,figure 4 and 5. The grey Images (32 frames), depth maps (32 maps), and the reference direction (current dx, dy for next 8 frames) are the input to the Lidar Model whereas the images and the reference direction are the input for the Image Model.

Long Short-Term Memory (LSTM)

An artificial recurrent neural network (RNN) structure used throughout the deep learning is long short-term memory (LSTM). LSTM has reinforcement links, unlike normal feed - forward networks. It really can approach not just to specific data points (as with images), and thereby total data streams (such as speech or video). For instance, for activities like un-segmented, linked handwriting recognition, speech recognition and anomaly - based in network traffic or IDSss, LSTM is relevant (intrusion detection systems).

Long Short Term Memory networks are a different sort RNN, likely to learn long-term interactions, typically only called "LSTMs". Hochreiter&Schmidhuber (1997) presented them, and many authors refined and popularized them in their subsequent work. They perform enormously so on a wide range of topics, and now are commonly used. LSTM was specifically designed to prevent the issue of long-term dependence.

Both recurring neural networks do have shape of a sequence of repeated neural network systems. This condition usually occurs will have a really basic structure, including a single tanh layer, in standard RNNs.

On a number of training sequence data, an RNN utilizing LSTM units may indeed be trained in supervised manner, using such an optimization technique, such as linear regression, mixed with back-propagation over time for calculating gradients required during optimization problem, in order to correct each weighted of LSTM network in relation to error relative (only at output layer of LSTM network).

Even so, within LSTM units, the error persists in the LSTM division's cell as relative error is back-propagated from either the output sheet. This "error carousel" constantly feeds variations to every one of the gates of the LSTM device unless they manage to turn the value off.

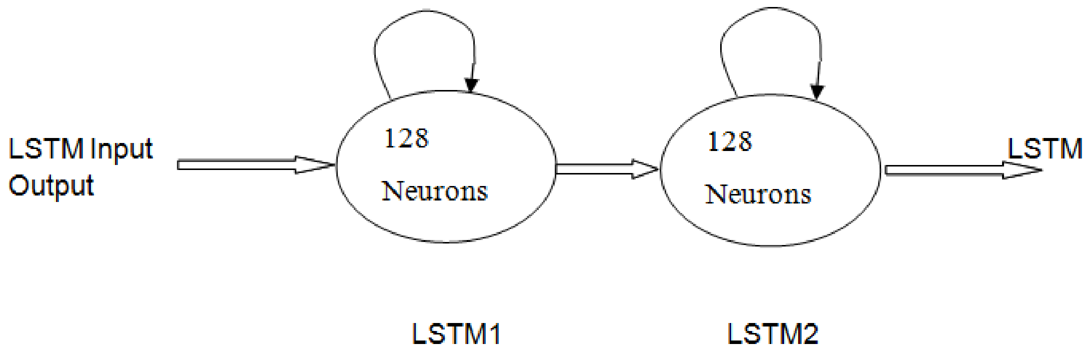

Figure 6: Block Diagram of LSTM Model

Dense Model

The name indicates that now the neurons in such a network layer are completely associated (dense) by layers. In a layer, each neuron collects an input from the all the neurons present inside this previous layer, however they are densely associated.

In many other sentences, the dense layer is a fully connected layer, indicating that all the neurons in a layer are linked to others in the next layer. A densely connected layer offers learning features from all of the pairings of the previous layer's characteristics, so that a convolutionary layer focuses on definite time frame with a minimal recurrent field.

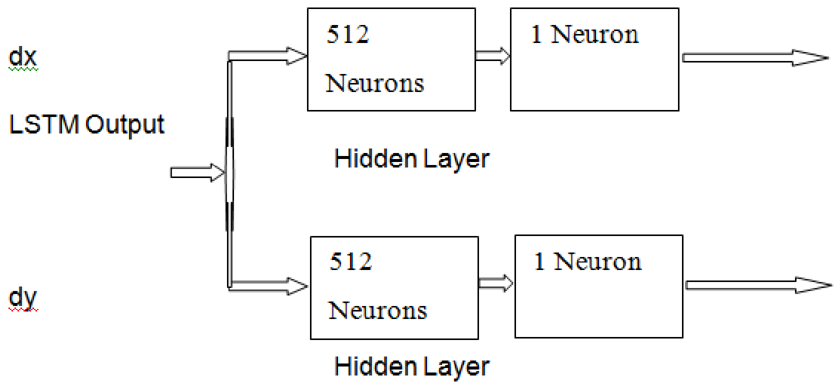

Figure 7: Block Diagram of Dense Model

3-D CNN

Regardless of what we claim, a CNN which is very close to 2d CNN, a 3d CNN continues to remain. Although the basic recommendations vary (non-exhaustive description): Initially, a 2d Convolution Layer is a parameter multiplication per entering here between input and the various filters, where even the 2d matrix elements are filters and interfaces.

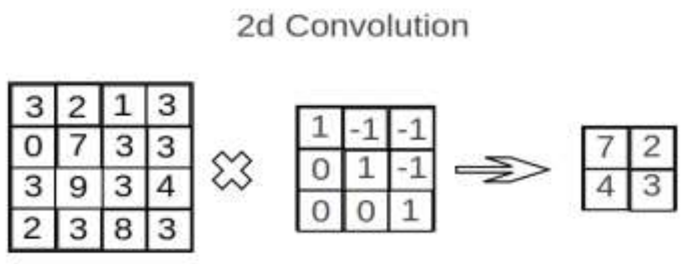

Figure 8: Example of 2-D Convolution

Having similar processes are utilized in a 3d Convolution Layer. On several pairs of 2d matrices, we do all these processes.

The advantages of 3D-CNN over conventional centralization based on finite-elements with reference to computational cost, quantitative evaluation of ambiguity and applicability of the systems are presented in succession. The outstanding features of the 3D-CNN methodology make it an useful framework alternative for promoting component design with quick iteration of product development and effective quantitative analysis of uncertainties.

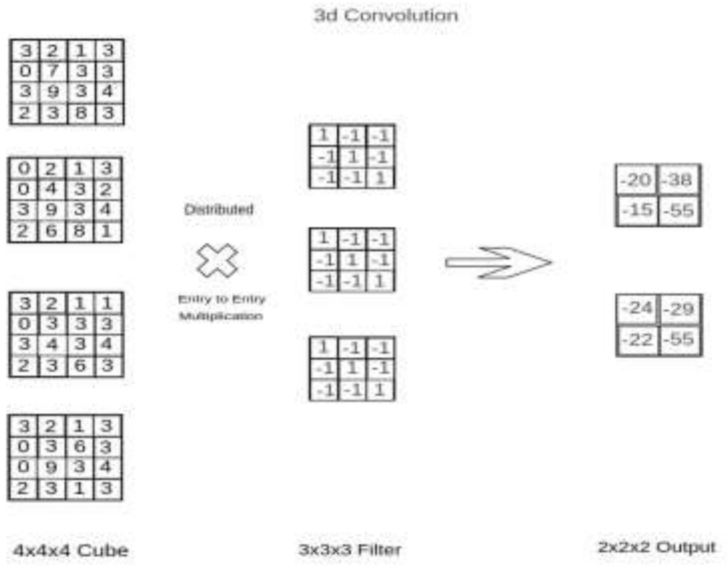

Figure 9: Example of 3-D Convolution

We're looking for a 3d Maxpool (2x2x2), the maximal component in a cube width 2. The whole cube signifies the space circumscribed from its input by the 2x2x2 field.

IV. RESULT & DISCUSSION

The aim of the project is to showcase that reduced computational delay using RFID instead of DIP can result in greater efficiency of resultant AVS. To justify the hypothesis, further literature reviews will be conducted to provide a greater context for the short-coming and advantages of both the systems. Furthermore, the theoretical models for both the systems will be evaluated in Python to obtain theoretical results.

The two (RFID and DIP) will be tested using a closed loop system to identify how they are corresponding to changes in the visual control. Their ability to track and monitor the changes in the visuals will be analyzed using various control theory techniques with relative response time calculations to prove how their computational times are varying. The difference in computational time delays along with accuracy of object detection will play a vital role in the validity of the study being conducted.

Approximately 100 variations of a clear route across Oxford, UK, recorded over a span of over a year, are in the Oxford RobotCar Datasets. The database includes many different environment, pedestrian traffic variations, together with longer-term modifications such as renovation and road operations.

Figure 10: Image of Oxford RobotCar Dataset

Oxford RobotCar Datasetdataset is very big.We have downloaded more than 2 TB data and it is less than 50% of the total.I consider all the dataset samples having a size of fewer than 150GB as test data.

https://robotcar-dataset.robots.ox.ac.uk/datasets/

I have used 70 percent of data for training and 30 percent data used for testing.

The original path of the car carrying different sensors is shown in blue color and the path predicted by Lidar Model is shown with red color in figure 11 similarly the path predicted by Image model is shown in figure 12. The comparison of the prediction results from Lidar Model and Image Model is shown in Figure 13.

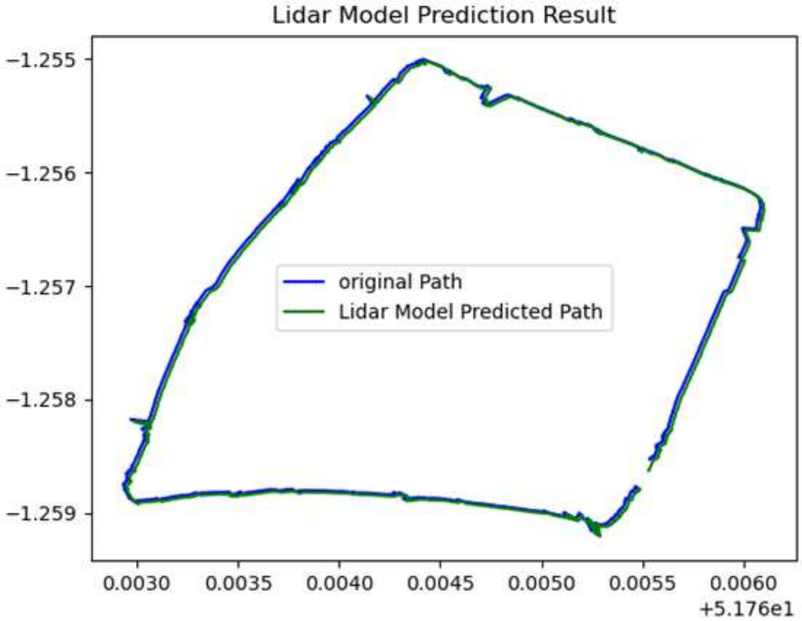

Figure 11: Lidar Model Prediction Result

In this above graph present as lider model prediction result, in this graph the car carrying different sensors is shown in blue color as original path and the path predicted by Lidar Model shown in green color. Lider Model Prediction is same as original path but lider prediction is very fast to image model.

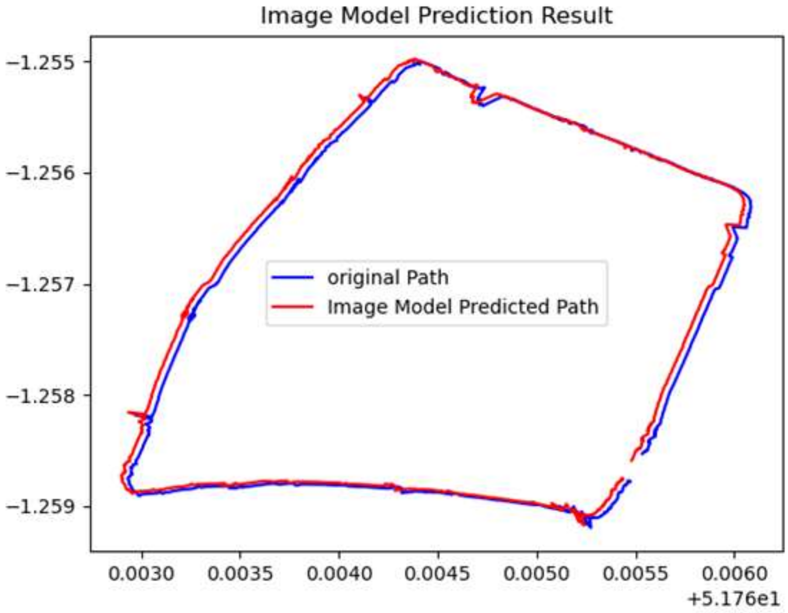

Figure 12: Image Model Prediction Result

In this above graph present as Image model prediction result, in this graph the car carrying different sensors is shown in blue color as original path,the path predicted by Lidar Model shown in green color and the path predicted by Image Model shown in red color.

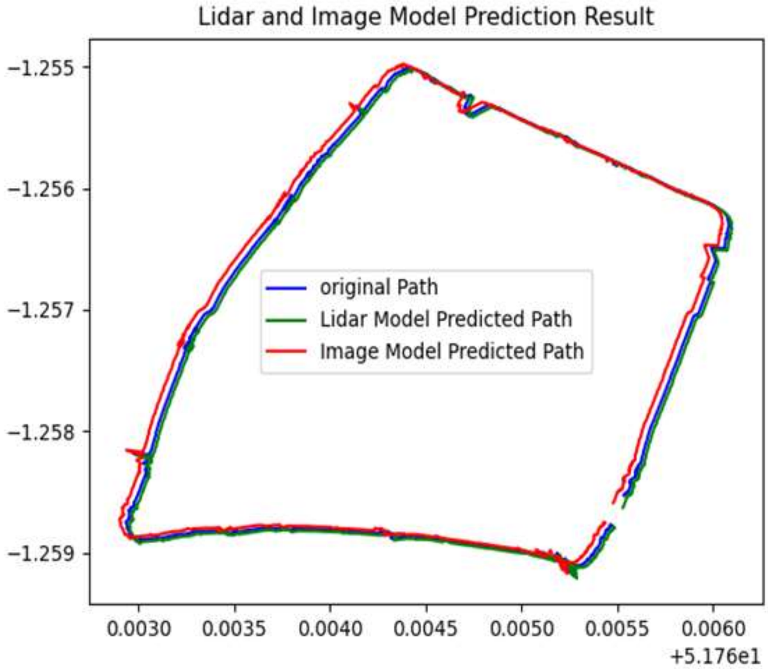

Figure 13: Lidar and Image Model Prediction Result

In this above graph present as comparison of original path, image model and Lider model prediction result, in this graph the car carrying different sensors is shown in blue color as original path and the path predicted by Image Model shown in red color. Lider Model Prediction is same as Image Model but Lider model prediction is more accurate to image model.

Table 1: Center Location Error of Model

Model	Center Location Error (GPS Unit)
Image Model	8.4542×10^{-2}
Lidar Model	1.7213×10^{-2}

In this above table to shown as center location error of Image Model and Lider Model. Center location error (CLE) occur error evolution plot of all visual trackers with the container image sequence. As per center location error showed Lider Model is more accurate to image Model.

V. Conclusion

For the purpose of this study, the weights of the trained version of our model have been applied to the problem of object detection and identification. The results of the model have been mapped with the data from the Lidar in order to determine the distance and angle of the object for the purposes of controlling the vehicle and navigating it. It has been seen that the Lidar data has been detecting the item for a relatively close distance with an error rate that is approximately 3.714 percent on average (2.5 to 5.5 meter). Therefore, the performance of the proposed work has been satisfactory for the detection and identification task. This work could be expanded by integrating the output of a vision and radar system with a control system of a vehicle for the goal of using navigation in a variety of different circumstances.

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