Chapter 1

Introduction

The modern technology is growing fast towards automating many things including the automotive system. When automated, it becomes essential to establish the communication between the vehicles on the road so that the obstacles on the road are communicated and the mishaps can be avoided. Through this chapter we will get to know brief about the vehicular communication systems and the literature behind it, Motivation and key outcome of the project.

1.1 Background

The development of countries mainly increases the traffic in major cities as well as roads. This leads to the various on-road mishaps one such being accidents. The below figure 1.1 shows the graph of the number of accidents and its outcomes. It is observed that there is no significant decrease in the outcomes and number of accidents even though many measures are taken. Hence, we propose a vehicle communication system as an effort to reduce such mishaps on the road.

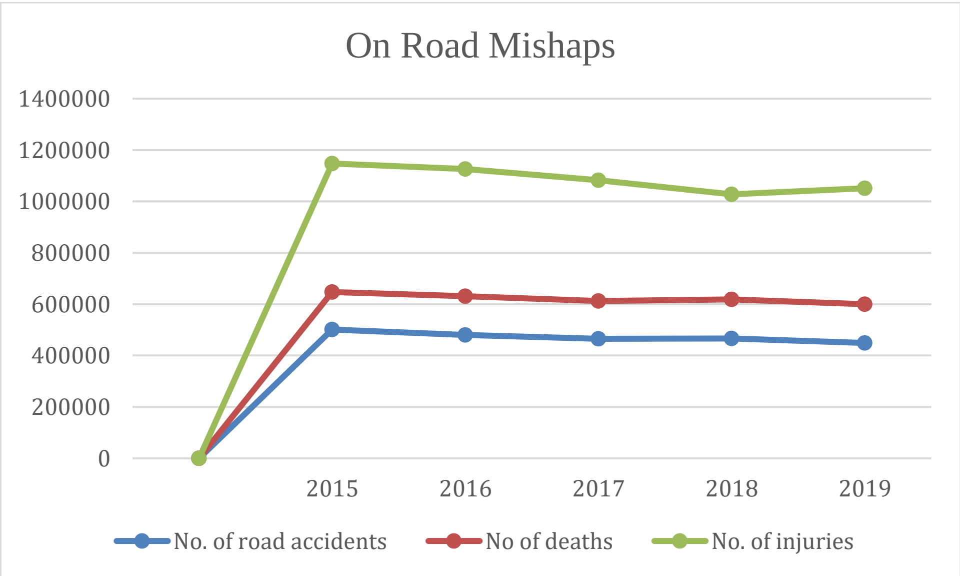


Figure 1.1 Statistics of On-Road Mishaps in past 5 years

Vehicle-to-vehicle (V2V) communications is a wireless communication network where automobiles communicate with one another about the obstacle on the road like cars, motorbikes ahead, people standing etc. as well as the current status of the vehicle which includes velocity of vehicle, location and the direction of travel, braking, and loss of stability of the vehicle. This helps in avoiding crashes/accidents, easing road congestions, and also improving environmental standards. The V2V communications target Automotive Industries, Smart Cities, etc. The V2V communication is as shown in Figure-1.2.

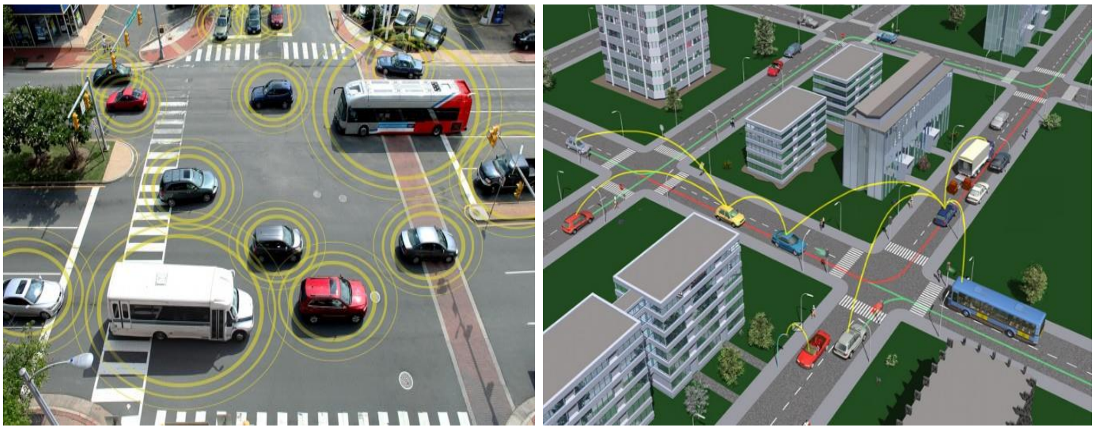


Figure 1.2 V2V Communication.

V2V technology uses dedicated short-range communications (DSRC). It is a standard defined by FCC and ISO. Sometimes it's noted as being Wi-Fi-like network because it uses 5.9GHz as one of the frequencies, which is used by Wi-Fi. The range can be defined up to 300 m or 1000 ft or about 10s at highway speeds. The V2V uses DSRC standards i.e., IEEE 802.11p, and cellular V2X standards i.e., 3GPP standards as LTE.

The use of VLC helps in the faster and communication. It has the following characteristics:

- Data communication uses visible light frequency in the range of 400thz to 800thz.
- Uses fluorescent lamps to transmit signals at 10Kbps and LED for up to 10Mbps.
- The range of coverage is up to 2km with a powerful light source.
- The receiver contains photo-sensitive material like photo-diodes, photo-transistors, etc. which provide multi-channel or awareness of multiple light sources.

- Colour Shift Keying (CSK) is used. It is a frequency and intensity modulation scheme for VLC. This is outlined in IEEE 802.15.7 standard.
- The modulated signal takes on an instantaneous intensity equal to the sum of intensities of the LED used.

1.2 Literature Review

[1] The work done in this paper deals with the V2V communications as an Intelligent Transport System (ITS). The necessity for the V2V communication as a fully automated process helps in decreasing the accidents on the road. Many topics like Scope, Vision, Communication models like- DSRC, IEEE802.11p etc are discussed. The basic idea as to how to develop a V2V communication system can be obtained from this research.

[2] The basic idea implementation of a V2V communication model can be obtained in this research. A frame work using LiFi as well as photodetector for transmission and reception and their working can be understood and a prototype of the blocks for a VLC transmitter and a receiver are studied in this research.

[3] An idea of co-existence of VLC with RF technology is discussed in this research. The need of optimizing the physical medium and research for the higher layers of the network architecture is the motivation in this research. An NS3 simulated network architecture is studied in detail and its implementation in indoor environment is studied.

[4] The research mainly deals with the detection and mapping algorithm od obstacles for the autonomous driving system in rural as well as off-road environment. A vehicular system configuration for sensing and detecting the on-road obstacles using LIDAR is used in this paper. The algorithm used is lane detection algorithm and the vehicle is designed to detect pedestrians, crossings and speed bumps on the road.

[5] A simulation model for V2V communication using VLC for a real-time scenario is proposed in this research. The usage of the tail lights as well as headlights of a vehicle as the source for transmission and reception of data is discussed. The simulation of V2V as well as V2I communication for crossroad and metropolitan scenarios is made and the channel characteristics is compared.

[6] A cellular network based on software defined networks (SDN) for V2V is researched in the paper. A scheme for data-offloading using vehicular ad-hoc networks

(VANET) is implemented using SDN and Mobile Edge Computing (MEC). The link establishment between then vehicles is monitored through a cellular network. The procedure: 1) uses each vehicle's information; 2) calculates and notifies the users in the network using centralized management strategy; and 3) establishes a VANET routing path for paired vehicles that are currently communicating with each other using a cellular network. The performance analysis is also made.

[7] The usage of off the shelf LED as well as Photodiode for transmitter and receiver is discussed in this research. The use of VLC as a cost-effective method for an integrated Intelligent transport system is the key area of interest. The use of already present lights and the reception of this leads to a low complexity and high reliable communication system between vehicles

In [8] development of a 10 Mbps VLC link that uses LEDs as both transmitters and receivers. The system uses binary OOK modulation without any equalization. Transmission distances exceeding 20 cm were obtained with a low power LED and no lenses. The throughput and transmission range are expected to much improve when using high power LEDs and more effective modulation formats.

In [9] research focuses on how to use VLC modulation schemes and probable ways of avoiding the interference from the surrounding ambience. Provided by recent advances in LED technology, IEEE 802.15.7 standard supports high-data-rate VLC up to 96 Mb/s. this is done using fast modulation of optical light sources which are dimmed during their operation. IEEE 802.15.7 standard provides dimming adaptable mechanisms for flicker-free high-data-rate for VLC.

In [10] an architecture for the V2V communication using Optical Camera Communication (OOC) is proposed in this research. Hybrid Spatial Phase Shift keying (HSPSK) is used as a standard modulation scheme for OOC. The AI based communication system is discussed. The is analysed to evaluate the performance of the proposed system over a complex channel model in a vehicular environment. The use of AI based decoder makes the approach a novel one.

In research [11] a method to separate the overlapping LEDs is proposed. The edges of the overlapping LED are detected using Canny edge detection algorithm. These edges are extracted based on contour mapping. Then the performance analysis is done for different scenarios.

Obstacle recognition based on depth images is widely studied [12]. Due to its advantages of 3D information and environment illumination insensitivity, the depth images are found to be most useful and accurate for the recognition. The traditional recognition methods mainly focus on hand-crafted feature design, which cannot achieve satisfactory results. The proposed methodology in this research informs about CNN method through which the obstacles can be detected.

The use of HAAR cascades for the face recognition is discussed in [13]. This uses deep learning and is used to recognize a person on the road. The recognition method uses CNN architecture for recognition of the faces. The extension of this cascade algorithm is done for the other objects like cars, truck etc, for the obstacle detection on the road. Though it yields acceptable results, the drawbacks like more false negatives are discussed in the research.

Depth-wise separable CNN are widely used for the recognition of objects with multiple features. The research [14] deals with the architecture of the same for the efficient analysis of the objects using depth-wise separable neural networks, and how is it is distinguishable from the regular neural networks. Aspects like false-positives and false negatives are also discussed in this paper.

A state-of-the-art method for object recognition from images is proposed in [15]. It deals with the concept of Octave Convolution for neural networks. Using OctConv in the neural networks helps in solving the redundant spatial problems raised due to the redundant feature extractions helping to improve the model efficiency.

The concept of YOLO – You Only Look Once is explained in [16]. This recognition algorithm mainly uses the GPU for the execution. The paper deals with how this algorithm can be run only using CPU for its execution to obtain better and accurate results. This gains the confidence and purpose for the systems which run on laptops and personal computers and don’t use graphical processors for their execution.

The usage of the object detection using YOLO is discussed in [17]. This algorithm is mainly used in autonomous driving systems and has 80 distinguishable classes for classification. It is mainly designed for such systems where the physical presence of driver is not required. This algorithm detects different objects in a single frame.

The concept of spatial pyramid pooling is explained in the paper [18]. This is exquisitely used in YOLO algorithm for the better recognition of the images. It is concluded to have better solutions for handling the different scales, aspect ratio and sized objects for recognition. It also helps in avoiding the different unwanted classification which lead to false positives and false negatives which reduce the accuracy and efficiency of the detection.

The modulation technique called CAP is discussed in paper [19]. Carrier-less amplitude and phase modulation is proven to be less complex and spectrally efficient for the VLC applications. The jitter timing for the transmission and reception of the signals can be reduced using CAP.

[20] deals with the system design of the VLC system using amplitude shift keying (ASK) methods. ASK is most simple and efficient method for modulation of digital signals. The VLC channel enables a large number of users to get access to the same channel. Hence ASK forms an efficient channel modelling which provides high data rate and spectral efficiency.

A price friendly Arduino – Mega based communication system for VLC is discussed in [21]. A hardware is developed to perform a VLC link using ambient sensor for communication and the results were verified. The system uses simple analogy circuits for communication. This is used for indoor VLC systems to which are used for internet of things (IOT).

A novel technique is called composite amplitude shift keying (CASK) is introduced in the research [22]. The idea solely depends on the nature of commercial LEDs which have multiple chips and controlling the chips using CASK. This results in the ASK modulated light emitting from the LED, making it easier for communication. The intensity control as well as the modulation support for the transmission of the signal is extensively.

Adaptive threshold detection for VLC is discussed in paper [23]. The usage of different geometrics and the frame structure is experimented for indoor VLC. It is concluded that the circular or hexagonal geometry in arranging the LEDs in the transmitter id much more efficient when compared to the use of the conventional – non coherent LEDs. Hence adaptive threshold calculations can be helpful to overcome the dynamic threshold in the system.

[24] deals with the communication using visible light to find the positioning of the objects in an indoor environment. The usage of a large number of LED for the transmission of position of the objects and reception of those information using Visible light receivers is discussed.

A voltage comparator for the VLC receiver is demonstrated in [25]. The performance evaluation of the system for up to 1m is experimented. The use of Manchester encoding for the data transmission made the communication easier. The results were verified in terms of the output luminous intensity.

A system for Vehicular ad-hoc networks is proposed in [26]. In the research, machine to machine technologies for the implementation of the vehicular communication is the main area. The usage of present technologies for the communication system is compared based on performance analysis.

In the research [27], various factors that affect the V2X communications is explored. The environmental factors which effect the vehicular visible light communication is discussed and the feasibility of V2X systems under such conditions is explained based on performance characteristics.

In [28] deep learning technique for optical vehicular communication is discussed. The technical issues and present technological conditions are considered for an optical camera communication for V2V communications. The system is based on AI decoders and error correctors to ensure maximum efficiency for the transmission and reception.

[29] is a survey of vehicular visible light communication. The paper talks about the various aspects of VLC as in the environmental considerations, technological feasibility and the hardware implementation.

[30] discusses the channel modelling for VLC. It also explains the performance evaluations of the of the VLC system by the using channel impulse responses. This is

used for the ray tracing. The proposed system in this research is characterized on the pathloss as a function of system parameters and weather conditions.

It can be observed from the above survey that the most of the applications of the VLC system is feasible for indoor communications. And the implementation of the same is challenging. This is in the aspects of establishing the communication link in the outdoor environment, design modelling, and noise regulation. In put research we propose a prototype that is feasible with outdoor environment at shorter distances.

1.3 Motivation

There are many on-road accidents on highways or roads because of discrepancy in driving or potholes etc. or due to lack of awareness of the road structure. As one can say, increase in the traffic leads to increase in the mishaps as well as congestion on the road. The below statistics show different predicted values of various on-road mishaps for the next four years in the figures 1.3a-1.3c. It may be observed a small deviation from the original data set and not much significant reduction in the injuries or deaths or accidents as predicted using Data Analysis Tool using Excel. Hence the proposal of a vehicular communication system for better road safety.

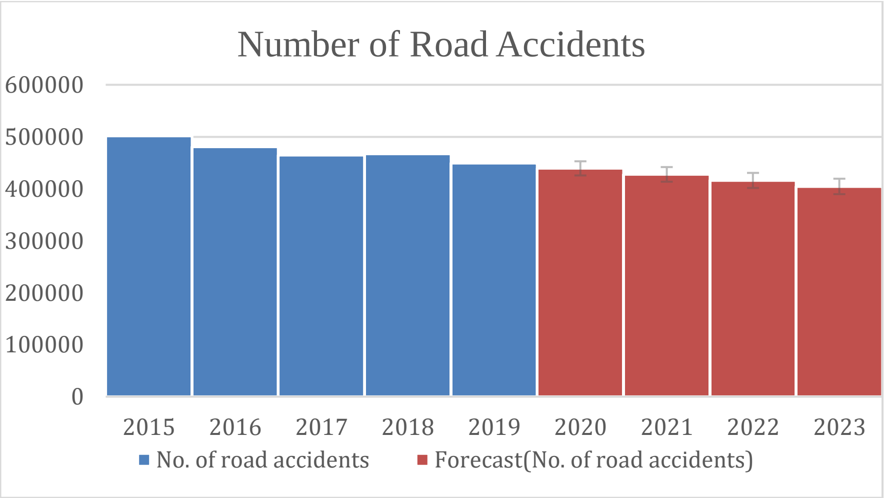


Figure 1.3a Forecast of number of road accidents

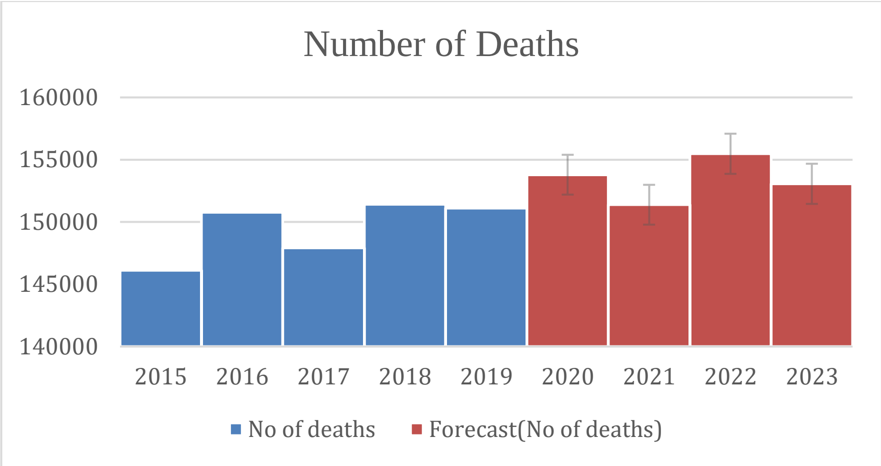


Figure 1.3b Forecast of number of deaths because of accidents on road

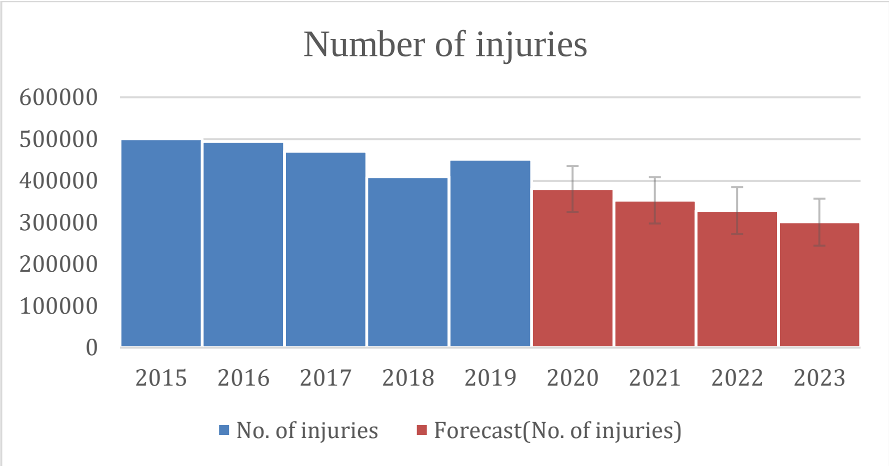


Figure 1.3c Forecast of number of injuries because of accidents on road

Industry demands innovation in the existing system.

- Kia, Mercedes and other high-end cars have scope for R&D in this area.

1.4 Problem statement

Since the on-road safety plays a majority role in developing countries like ours, we have to concentrate towards the betterment of vehicular communication. In order to avoid the on-road accidents, we can **"Design of a Vehicle-to-Vehicle Communication System using Visible Light Communication"** for a reliable on-road Security.

1.5 Objectives

The project mainly focuses on design and development of transmitter and receiver modules of vehicular communication system (VCS). This can be achieved through the following objectives:

- To detect various on-road obstacles such as vehicles, speed brakes, traffic signals, animals etc.
- To process the obtained data and classify to respective classes (animals, cars, etc).
- To develop a prototype of Vehicular Communication System (Tx and Rx).
- To estimate crashes/ accidents, road congestions.
    - Performance evaluation of the complete system with respect to delay, throughput, packets loss indicator

The key outcome of the project is probable design, development and implementation of robust VCS to avoid crashes/accidents, easing road congestions and also improving environmental standards.

1.6 Challenges

In a developing country like India, challenges one can face for proper vehicular communication system is the traffic density. In cities Bangalore, Mumbai. Chennai, Delhi etc, the traffic increases as the days roll by. Therefore, a better management system needs to be proposed. In order to bring in the system into action, the change in the automotive domain is must. Hence the change of automotive domain throughout the country becomes a challenge. The number of vehicles is more hence it takes more time to incorporate the system as well as the people are not so welcoming to the changes that will be proposed.

1.7 Methodology

The basic idea of the project is to indicate the driver and drivers in the proximity of the transmitting car(transmitter) about the probability of accidents, obstacles or congestion on the road hence preventing the mishaps. The basic flow for the transmitter section is as shown in the figure 1.4.

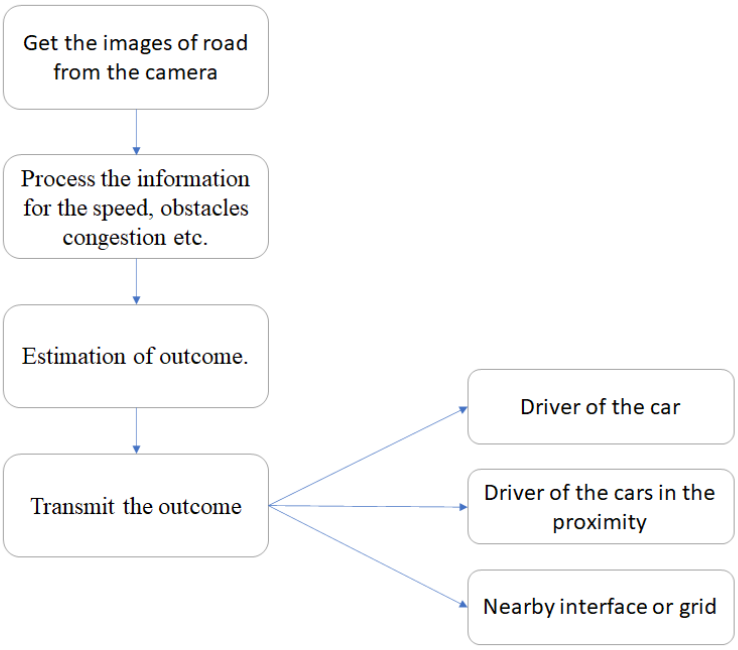


Figure 1.4 The basic flow for the transmitter section.

A camera is fit onto a car which captures the live video of the road. The captured video is processed to detect the obstacles on the road like- Speed Breakers, Humps, Animals and most importantly other vehicles. The processed data is then used to estimate the outcome mainly the speed of the vehicle, if the situation leads to an accident or not, basically estimating the road safety. The estimated output is transmitted through a visible light communication link. Using the data received by the vehicles and vehicles in the proximity of the transmitting vehicle, the required action can be taken.

1.8 Organization of the thesis

- Chapter 1 deals with the overview of the project briefly discussing project specifications, objectives and scopes also motivation and problem statement.
- Chapter 2 discusses the key topics and theory behind the project.
- Chapter 3 explains about the work done and methodology used for the implementation of the system.
- Chapter 4 discusses the results obtained and the performance measures.
- Chapter 5 deals with the conclusions and future scope for the project work done.

Chapter 2

Theory and Concepts

The basics of any research is the theory and concepts behind the research. The extensive survey is the key to any research thesis. This chapter is informative about the key concepts used in the research thesis.

2.1 Visible Light Communication

Visible light communication refers to the usage of visible light frequencies for the communication purposes. The frequency ranges from 400thz to 800Thz. Figure 2.1 represents the visible light spectrum (VLS). The VLS ranges from 380nm to 780nm and has bandwidth of about 400THz.

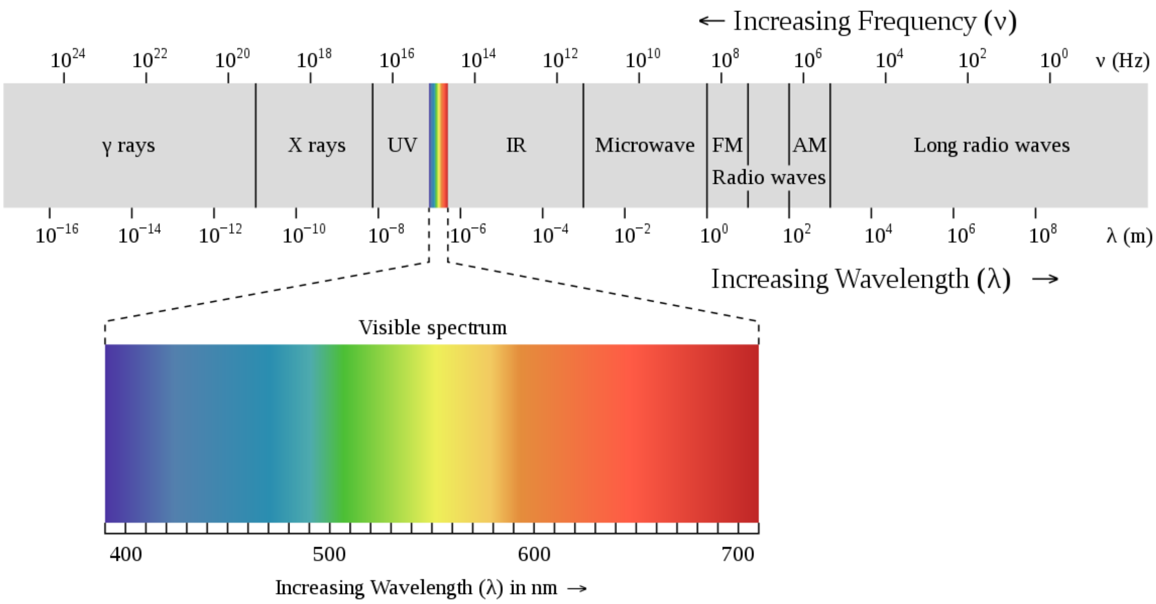


Figure 2.1 Visible light Spectrum

2.1.1 IEEE 802.15 TG7 for VLC

The PHY and MAC layers for short-range optical wireless communications, using visible light in optically transparent media is defined by IEEE 802.15.TG7 standards. The wide bandwidth for VLS extending from 380nm to 780nm provides for the better communication. IEEE 802.15.TG7 delivers data rates sufficient to support audio and video multimedia services. The mobility of the visible link, compatibility of visible light communication for infrastructures where external noise factors, and interference from other sources are key points of research.

VLC devices are classified as infrastructure, mobile, and vehicle-mounted. The standard supports both one way and two-way communication of data, with point-to-point or point-to-multipoint connectivity. VLC supports peer-to-peer, star, and broadcast topologies for communication. An error rate probability of 8% is expected from the communication setup. Research for lesser error rate is also in progress. The packet size chosen for transmission is 256 bytes for low data rate applications and 1024 bytes for high data rate applications. VLC transmits data by intensity modulating optical sources such as LEDs. Some of the key features of this standard include

- Star or peer-to-peer operation for communication.
- Optional guaranteed time slots for data on-loading and off-loading.
- Random access with collision avoidance.
- Acknowledged transmissions.

The PHY supports the following modes:

- Type-I: intended for ranges of tens of meters and low data rate (tens of Kbps) applications.
    - Modulation in this type is ON/OFF keying (OOK) and variable pulse position modulation (VPM).
- Type-II: intended for ranges of tens of meters and moderate data rates in the order of 10s of Mbps. This type supports colour shift keying (CSK)-based modulation as well as OOK and VPM.

2.1.2 Data that can be transmitted using Visible Light Communication

The transmission of data over a VLC module basically, a LiFi module, is basically classified as DSRC, distance range varying up-to 2Km. The types of data that can be transmitted using VLC includes: Location, Speed Direction, Traffic Ahead, Obstacles etc. as shown in fig 2.2. When using the VLS for the communication, we use lightfidelity (Li-Fi) for the communication purpose. It consists of two main blocks mainly transmitter and receiver.

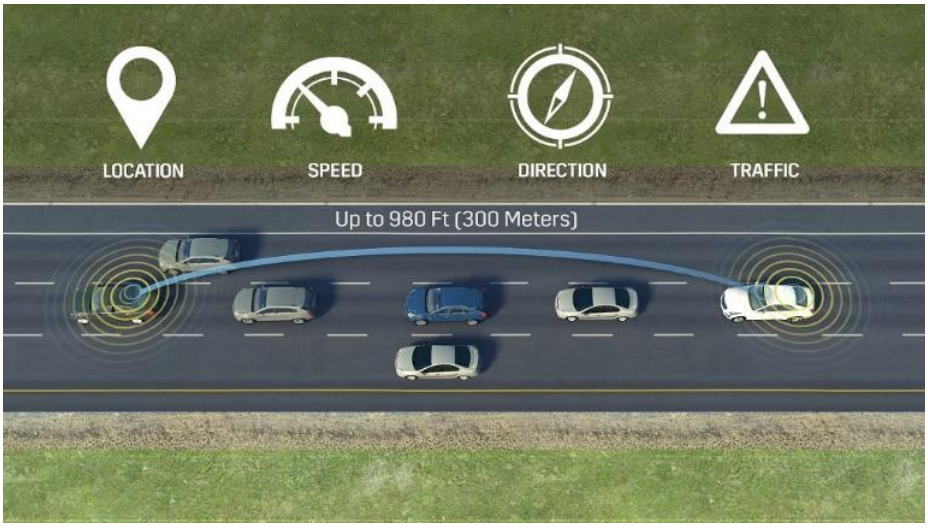


Figure 2.2 Varieties of data that can be transmitted using VLC

2.1.3 LiFi Transmitter and Receiver

Li-Fi transmitter and receiver are crucial elements of the V2V communication system using VLC. Design of the transmitter and receiver for the application is one of the most interesting as well as educative task.

Figure 2.3 (a) shows the LiFi transmitter. The input data (in analog form) is converted to binary (in digital form) using an ADC. The converted digital data is given to a LED driver. The on-off keying modulation is employed to send the data i.e.; the high illumination LED is turned on and off progressively depending on the input. The LED converts the electrical signal to light signal. This light is transmitted wirelessly trough the communication channel.

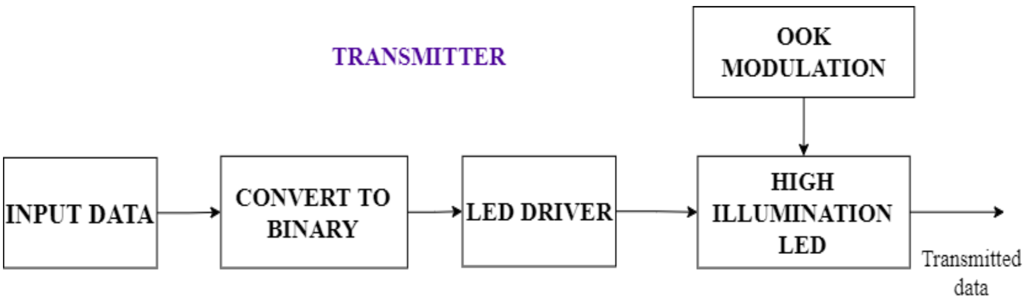


Figure 2.3 (a) LiFi Transmitter

Figure 2.3 (b) represents the basic block diagram of the LiFi receiver. The transmitted data from the transmitter is sensed using a photo detector like LDR, photo diode or photo sensor panels. This converts the received light signal to electrical signal. The received signal is demodulated and decoded using OOK demodulation. OOK demodulation is synchronous to that of the OOK modulation in the transmitter. Due to the signal interference in the channel, the signal is passed through double stage inverted amplifier which acts as buffer amplifier. The binary data obtained at the end of the amplifier is converted to original analog data by using DAC and Filters. The output of obtained is the original signal.

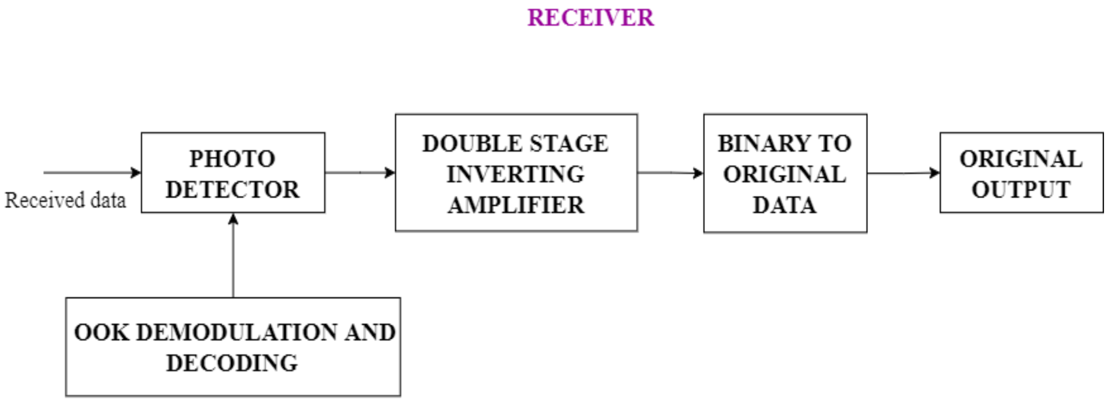


Figure 2.3 (b) LiFi receiver

2.1.4 Advantages of VLC

Visible light communication offers the following advantages over the existing communication systems.

- No electromagnetic radiation exposure. Interference with radio systems is nil.
- Data transmission with commercially available high-power LED lamps. Transfer rates of up to 3 Gbps.
- Combination of lighting and data communication.
- Parallel operation of several VLC systems possible.
- Optically opaque surfaces make data protection easy.
- Transmission standard IEEE 802.15.7.
- Consumes low power and efficiency is high. No power amplifiers required for the setup. Hence it is cost effective.

2.2 Vehicle to Vehicle Communication

V2V communication basically enables the communication between two or more vehicles in the same lane or in adjacent lanes within the proximity of the transmitting vehicles. It facilitates the automatic applications such as roadway information, safety services, highways and autonomous driving.

The usage of VLC for V2V is one of the hot and trending topics in modern research work like implementation for autonomous driving systems, automatic cruise control systems, V2I, V2X, V2G communications etc. The implementation of V2V communication is as shown in the figure 2.4.

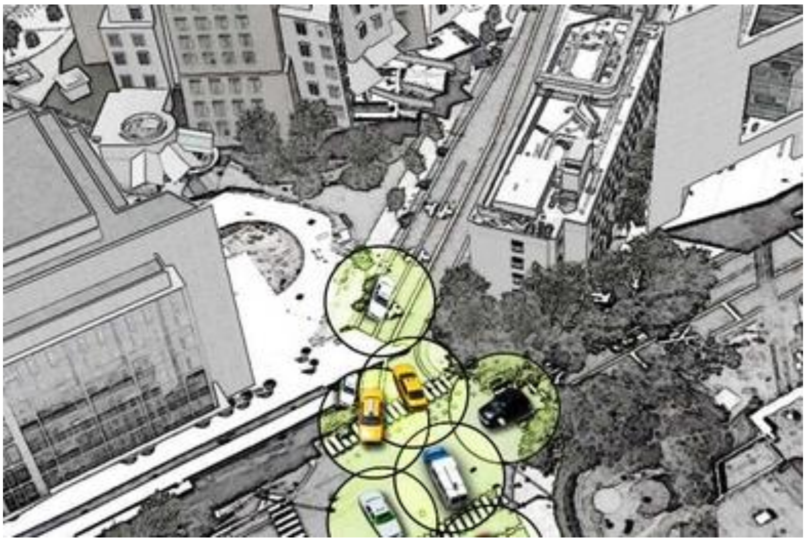


Figure 2.4 V2V communication at an intersection.

2.2.1 Vehicular Communication

The V2V communication commonly known as vehicular communication is one of the most researched topics in the present-day automotive industry. This helps in the development of self driven cars as well for the communication of the on-road obstacles to the drivers in the proximity. One of the most efficient way of doing this is by using Visible Light Communication. As discussed in the earlier chapters, VLC is promising and is considered as the future of communication. Though there is extensive research going on in this field, it will be implemented in the near future.

Figure 2.5 represents the vehicular communication module proposed in the thesis using LiFi modules. A camera is connected to the front of the vehicle through which real-time video of the road is captured. This captured video is used in an object detection algorithm. This algorithm detects the on-road obstacles like cars, person, truck, bus etc. And sends it to Arduino NANO in binary form. Arduino NANO is programmed for OOK and Encoding of the data and sending it through the channel as light signals.

At the receiver end a photosensor is placed and it senses the transmitted light from the transmitter and feeds the output to VLC receiver. The receiver, the converts the received signal into electrical signal and gives it to Arduino NANO. Arduino NANO is programmed for the decoding of the information. Once the information is decoded, it is displayed on the display device, say LCD display.

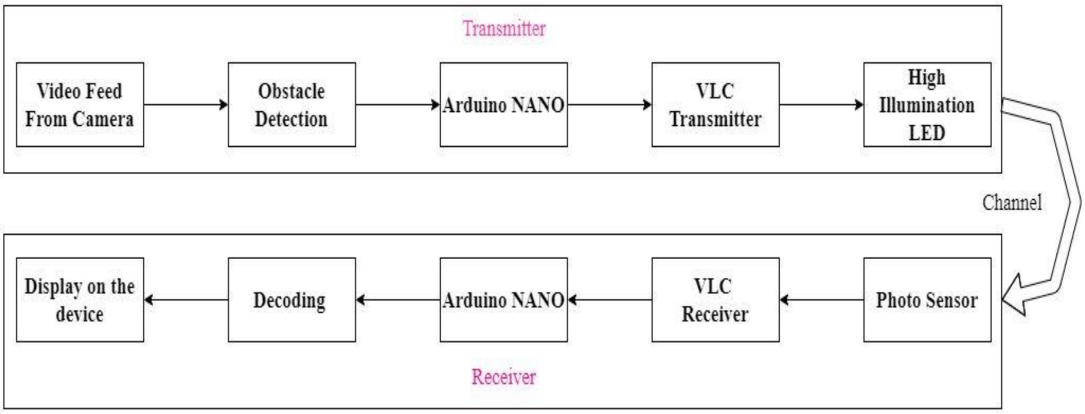


Figure 2.5 Block Diagram of Vehicle-to-vehicle communication using LiFi modules.

2.2.2 Amplitude Shift Keying for LiFi - Communication

Amplitude Shift Keying (ASK) on modulation techniques which can be used on digital data. This represents the data as variation of amplitude of carrier wave of certain frequency f_c. Amplitude Shift Keying is one of the easiest ways to modulate digital data. A requires amplitude is set as a threshold value for modulation. The 1s and 0s will be modulated according to the threshold values. The modulated value greater than the threshold value is considered 1 and modulated value less than threshold is considered as 0.

Figure 2.6 represents the ASK for the data: 101100101. (i) represents digital data. (ii) represents the carrier wave if frequency f_c. (iii) represents the ASK modulated wave.

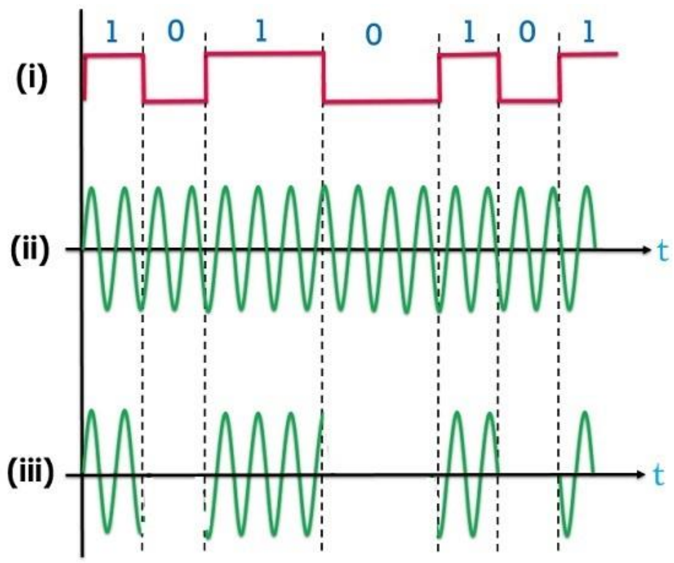


Figure 2.6 ASK Modulated Wave

The use of ASK for modulation as well as demodulation is fund to be inexpensive when compared to other. The use of ASK in the LiFi module is to turn on and off the transmitter LED to transmit the information. The light pulse generated by the LED carries the information. Similar to the transmission of morse code, on-off keying is used except that the on-off keying is used to turn on or off the LED. The time of the pulse helps in decoding the data and also helps in transmitting data accurately.

2.3 Convolutional Neural Networks (CNN)

CNNs are most widely used in training of images. CNN are in-fact advantageous as they consider images in the form of vectors and constrain their architecture in the most efficient manner. CNNs are arranged in three dimensions, i.e., width, height and depth.

For CIFAR-10 , the dimensions are 32 X 32 X 3. i.e., the width of the image is 32 units and the height if the image is 32 units and depth of the image is 3 units. In CNN, the depth is considered to be the third dimension rather than the number of layers in the network. The neurons in CNN are connected only to the required layers of the network, instead of being a fully connected network. Hence the final layer will have a lesser number of dimensions yielding to lesser weights when compared to a regular neural network. When using regular neural networks, the image size for a CIFAR image would be 32 X 32 X will be 3072. Hence, we need 3072 weights for the neural network to perform well. This may be possible and not be burdensome. But as the dimensions increase, the number of weights also increases which can prove to be quite burdensome and the fully connected network could be over fitted as many parameters could be wasted. The output layer of CNN for the same CIFAR- 10 image would have dimensions 1X1X10. Therefore, by the end of CNN. A full-scale image is converted into a vector containing class, scores, arranged along depth dimension.

2.3.1 Layers of CNN

Neural Networks receive an input and transform it through a series of hidden layers. Each hidden layer is made up of a set of neurons and each neuron is fully connected to all neurons in the previous layer. The neurons in a single layer function completely independently and do not share any connections. The last fully-connected layer is called the "output layer" and classification represents the class scores.

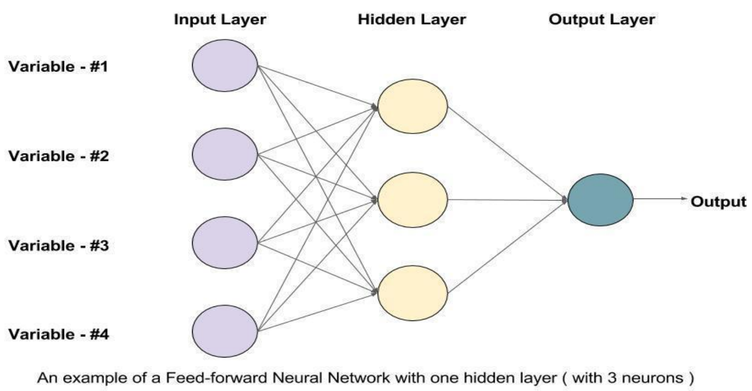


Figure 2.7 Regular Neural Network

The Figure 2.7 shows the regular neural network with an input layer, a hidden layers and an output layer. The number of weights required = 4.

Convolutional Neural Networks take advantage of the input which consists of images and they constrain the architecture in a more sensible way. In particular, the layers of a convnets have neurons arranged in 3 dimensions: width, height, depth.

The figure 2.8 shows how the regular network is converted into a single new vector. CNN arranges the neurons in three dimensions- width, height and depth. Every layer of a CNN transforms the three-dimensional input to a three-dimensional output upon neuron activation.

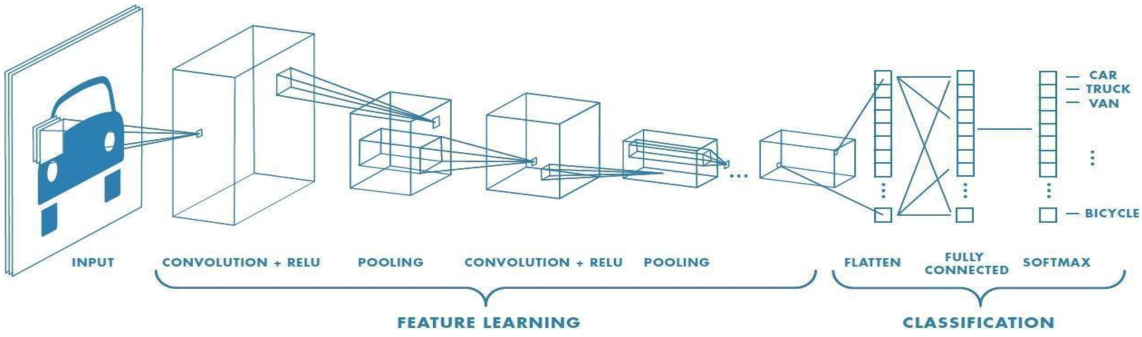


Figure 2.8 Convolutional Neural Networks

The layers of CNN as shown in the figure 2.8 are Explained as below.

1. INPUT Layer is of the dimension 32x32x3. It holds raw pixel values of the input image or video.

2. CONV or convolutional layer will compute the output of neurons that are connected to local regions in the input. It computes a dot product between the weights and region they are connected to in the input volume. This yields in lesser number of weights required throughout the neuron.

3. ReLU layer also known as rectified linear unit layer will apply an element wise activation function, such as the max (0, x) thresholding at zero. This leaves the size of the volume unchanged and easier classification of the objects.

4. POOL layer will perform a down sampling operation along the spatial dimensions. It acts as a filter of size 2X2 and is applied on the input image. It determines the exact location based on the specific feature of the original input. The weights are reduced by 3/4th of the original number which helps in controlling overfitting of the dimensions and reducing controlling cost.

5. Fully connected layer will compute the class scores, where each of the objects correspond to a class score. As with ordinary Neural Networks and as the name implies, each neuron in this layer will be connected to all the numbers in the previous volume helping in accurate classification of objects.

Convnets transform the original image layer by layer from the original pixel values to the final class scores. Note that some layers contain parameters and others don't. In particular, the CONV/FC layers perform transformations that are a function of not only the activations in the input volume, but also of the parameters (the weights and biases of the neurons). The RELU/POOL layers will implement a fixed function. The parameters in the CONV/FC layers will be trained with gradient descent so that the class scores that the convnets computes are consistent with the labels in the training set for each image.

2.3.2 Adaboost Classifier Algorithm

Ada-boost classifiers combine weak classifier algorithms to form strong classifiers. A single algorithm may classify the objects poorly. But if we combine multiple classifiers with selection of training set at every iteration and assigning the right amount of weight in final voting, we can have a good accuracy score for the overall classifier. In short Ada-boost, retrains the algorithm iteratively by choosing the training set based on accuracy of previous training. The weight-age of each trained classifier at any iteration depends on the accuracy achieved.

2.3.3 Cascade Classifier

Training of the Neural Network is done using Haar-Cascading weights. Haar-Cascading algorithm is a Machine Learning Classification algorithm. It is used to identify objects from a video or an image. In this algorithm, the cascade function is trained using many positive and negative samples, the objects which are not to be detected.

The Haar Cascade Classifier is trained in four stages. Each stage performs dedicated function helping in the reduction of the number of weights required for the classification of the objects.

2.3.3.1 Feature Selection

Feature selection is the basic and first step in any CNN based image processing. It is a pre-processing step which eliminates the unwanted features in the image. The image when pre-processed for Haar features tends to yield better accuracy of detection.

This feature detects and considers the adjacent rectangular regions in the given image segment, and it adds to the pixel intensities every image and calculates the difference between the two sums. The calculated difference is used for the classification and weight calculation. The figure 2.9 has shown the Features in the process. The features are of three types – Edge feature, line feature and centre round feature. The selection of these features results in better classification of the obstacle.

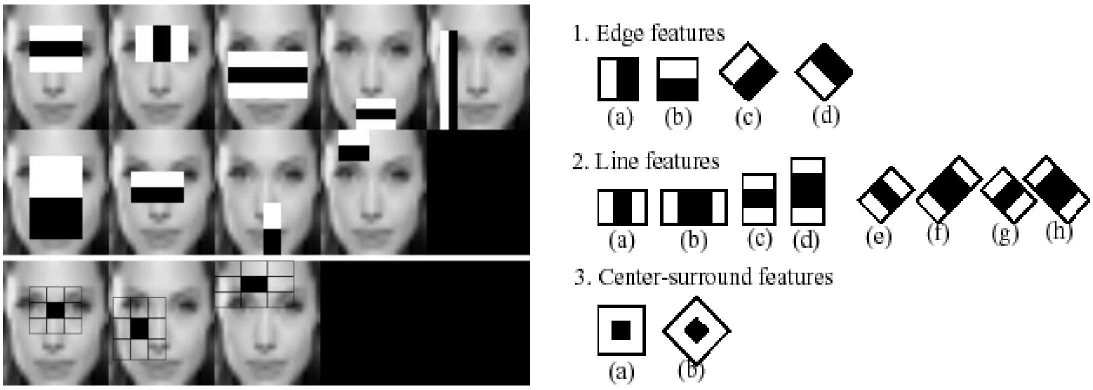


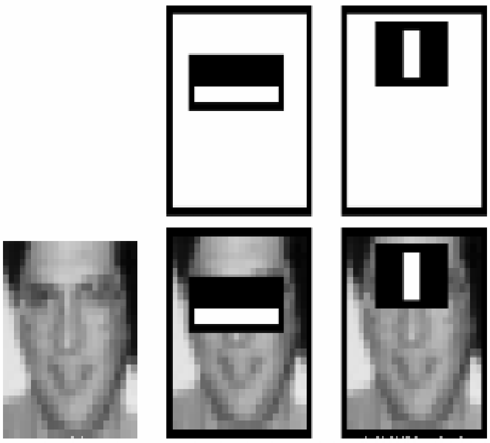
Figure 2.9 Features

$$F(haar) = \Sigma F(white) - \Sigma F(black) \tag{1}$$

Where, ∑f(white) is the number of pixels in white region, ∑f(black) is the number of pixels in black, F(haar) is haar feature.

2.3.3.2 Creating Integral Images

Integral Images boost the speed of the classifier. It makes the computations super-fast. The Figure 2.10a and Figure 2.10b represents how an integral image is formed. Row a represents the feature to be selected and row b represents how the selected feature can be used to implement the feature selected on the face. Example, Edge feature can be used to represent eyes and Line feature can be used to represent nose and forehead.



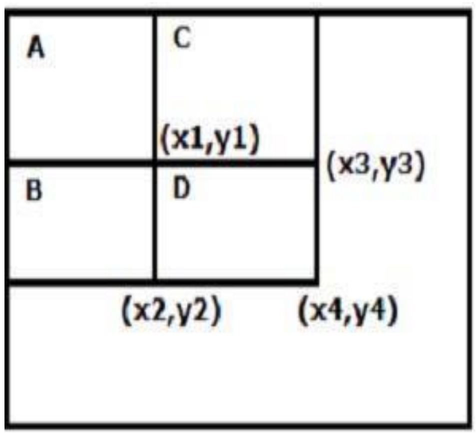


Figure 2.10 (a) Integral Images

Figure 2.10 (b) Integral images calculations

$$Sum = (D + A) - (B + C) \tag{2}$$

$$Sum = \left((x4, y4) + (x1, y1)\right) - ((x3, y3) + (x2, y2)) \tag{3}$$

2.3.3.3 Adaboost Algorithm

This algorithm is used to select best features out of many features and to train the classifiers depending on the performance. This algorithm creates a very robust classifier by linearly combining the simple weak classifiers with weights. Figure 2.11 represents the graph of sigmoid function used in Adaboost Algorithm.

$$H(X) = sign \sum_{t=1}^{t} \alpha_t . h_t(x) \tag{4}$$

$h_t(x)$= output of weak classifier

α_t= weight assigned to a character and it is given by:

α_t=$0.5ln((1 - E)/E)$, where E= Error rate (5)

Weight is updated using the formula:

$$D_{t+1}(i) = D_t(i)\, exp(-\alpha_t h_t(x_i))/Z_t \tag{6}$$

Where, $D_t(i)$= weight of ith sample and Z_tIs sum of all weights

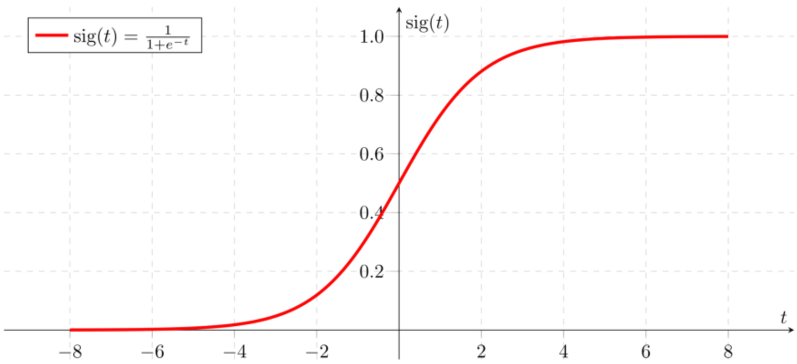


Figure 2.11 Sigmoid Function

2.3.3.4 Cascade Classifiers

These classifiers are collections of many stages. Each stage represents a weak classifier commonly referred to as decision stumps. These decision stumps are trained by using Boosting Technique, which has the ability to train a highly accurate classifier which uses a weighted average of the decision made by the decision stumps as shown in figure 2.12.

The stages of the classifier are given by current locations of the sliding window. The stages may be positive or negative. As shown in the table 2.1, it can be inferred as, when an object is detected, the region is considered to be positive and when there is no object detected, the region is considered to be negative. When the classifier detects a negative region, the classification is said to be complete, when the classifier detects a positive region, it is passed on to the next stage. When the final region is detected as positive, the detector reports the object as found. There are some cases where a classifier might give an error with respect to classification.

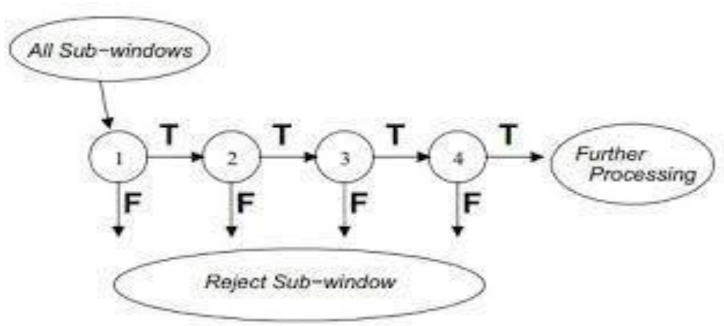


Figure 2.12 Cascade Classifier

Table 2.1 classification parameters

Classification	**Parameters**
Positive	Object detected and recognized
Negative	Object not detected and not recognized
False Positive	Object not detected but recognized
False Negative	Object detected but not recognized

The use of Cascade Classifier as a detection algorithm in real time is considered tedious as well as not of much accuracy. Hence YOLO algorithm is used to detect objects in real time.

2.4 You only look once-YOLO

YOLO is a robust real time object detection algorithm mainly to detect on-road obstacles precisely. It is a deep-learning algorithm for image recognition. It comprises of interconnected “one-stage detectors”. Figure 2.13 represents the one stage detector of a YOLO algorithm. The input is given to the backbone layer- in which required feature are extracted from the test image/video using pretrained models like ImageNet, ResNet, DenseNet etc. These algorithms are used to produce more efficient models for image recognition. The neck layer of the one-stage detector helps in obtaining the feature map of the extracted features at different stages of the backbone layer. The YOLO algorithm uses Featured Pyramid Network (FPN) as the neck layer. The recognition of the objects is mainly done in the dense prediction layer which is commonly known as head layer. This layer uses regression to predict the recognised object. The cost function of this regression is given by Mean square error factor –

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 \tag{7}$$

Where, MSE = Mean Square error, $\hat{y}_i$ = predicted value, y_i = expected value,

N = number of samples

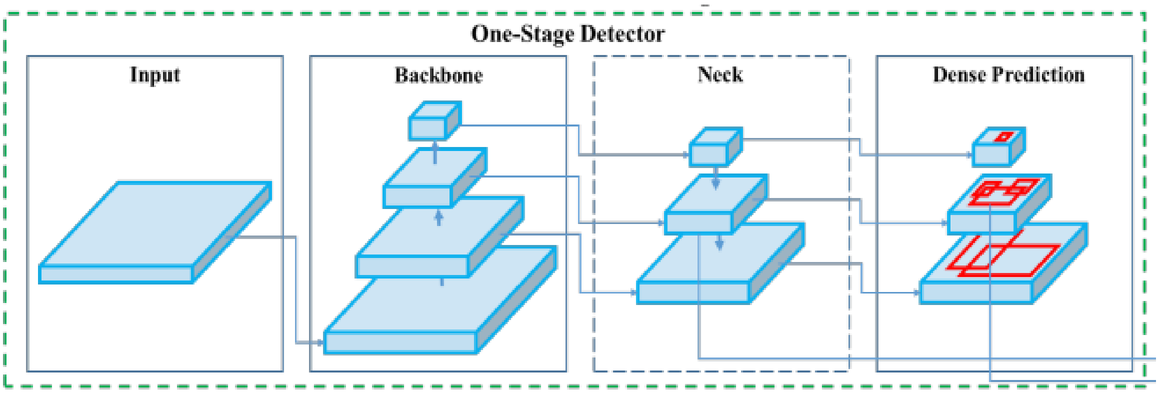


Figure 2.13 One-Stage detector of YOLO algorithm

2.4.1 YOLO V4 Algorithm

YOLO Version 4 (V4) algorithm is one of the advanced algorithms in YOLO generations. The algorithm can identify up to 80 classes including cars, bikes, person, animals, dog. The use of this algorithm helps in better recognition of the objects on the road with maximum accuracy.

2.4.1.1 Backbone layer:

The backbone layer of the YOLO V4 algorithm has two variants.

1. GPU Variant: This runs on Graphical Processing Unit (GPU) of the system. It uses CSP darknet as feature extraction model.
2. VPU Variant: This runs on Visual Processing Unit (VPU) of the processor. It uses EfficientNet Lite-MixNet-GhostNet/MobileNet as feature extraction models.

For feature extraction the backbone of YOLO V4 algorithm uses

1. Bag of Freebies (BoF) which includes CutMix, Mosaic data augmentation, DropBlock regularisation, Class label smoothing algorithms.
2. Bag of Specials (BoS) which uses Mish Activation function, Cross-stage partial connections (CSP) and multi input weighted residual connection (MiWRC) algorithms.

2.4.1.2 Neck layer:

The neck layer of YOLO V4 algorithm uses Spatial Pyramid Pooling (SPP) and Path Aggression Network (PAN)

1. Spatial Pyramid Pooling: It is an intuitive design for a neural network to perform feature mapping. The convolution layer is fed with the input from backbone layer. The convolution layer performs the convolution just like the CNN and the features are mapped according to biases, scale, mean, variance and weights. The mapped features are again modified with selected weights and then it is pooled in max pooling layer.

The use of SPP helps in handling different scales, aspect ratios and sizes of the test data and also has a very high accuracy for detection or classification especially when using Deep Neural Networks (DNN). Figure 2.14 shows the brief of how SPP in a network is implemented.

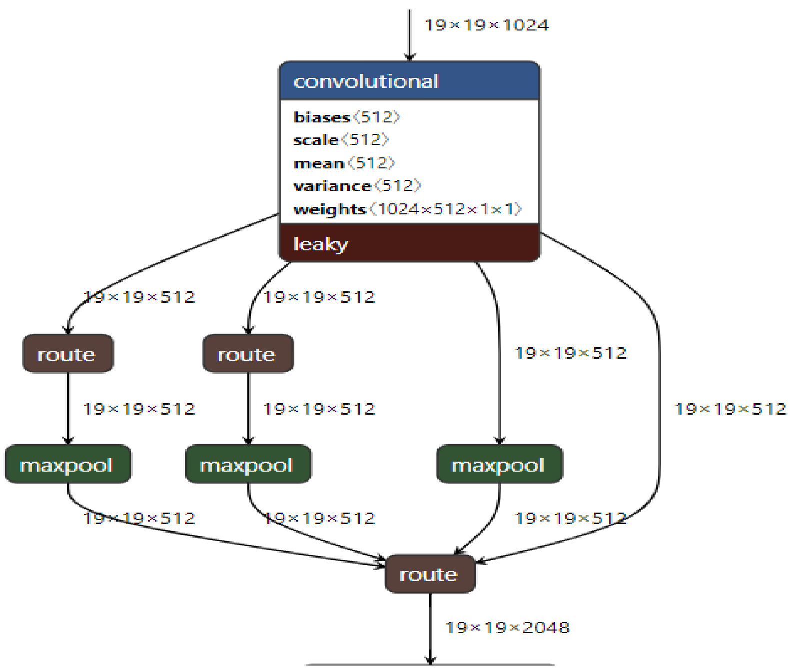


Figure 2.14 Spatial Pyramid Pooling

2. Path Aggression network (PANet): This helps in instance segmentation by preserving the spatial information. The main properties of PANet includes: bottom-up path augmentation, adaptive feature pooling and fully connected fusion.
    a. Bottom-up Path Augmentation: This helps in shortening the neural network path by taking bottom-up path to mask feature of large objects in the network as shown in figure 2.15.

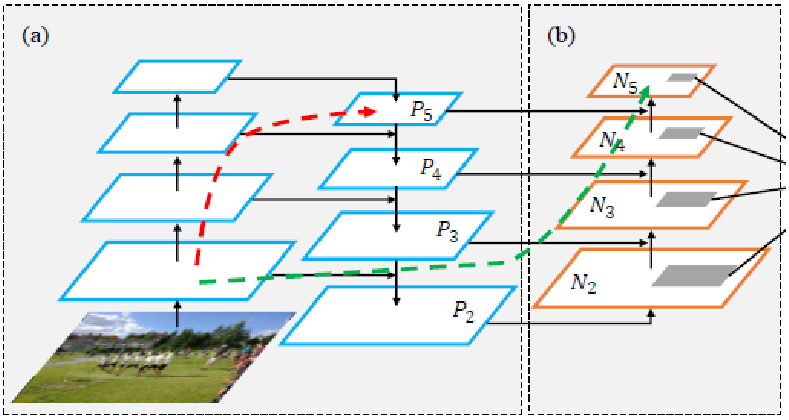


Figure 2.15 Bottom-up Augmentation

    b. Adaptive Feature Pooling: This is used to pool features in a very efficient manner. The PANet performs the ROI Align operation on each of the extracted feature which is then followed by element-wise max-pooling operation. This enables the network to be adaptive to new features while detecting the object. Figure 2.16 represents Adaptive Feature Pooling layer in YOLO V4.

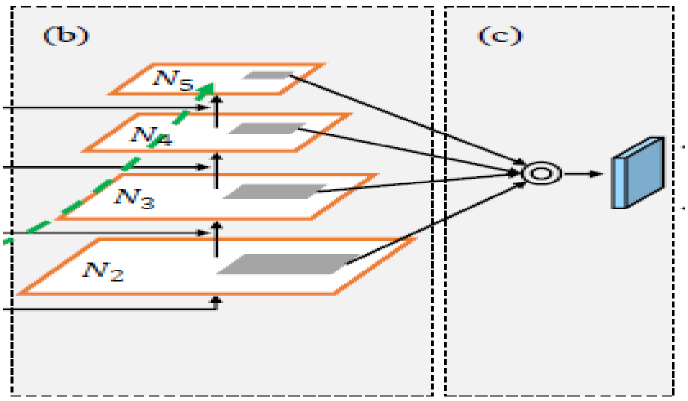


Figure 2.16 Adaptive Feature Pooling

    c. Fully Connected layer: The PANet uses fully connected later as they are location sensitive and can be adapted to different spatial locations of the object. Figure 2.17 shows the fully connected layer of PANet.

The use of PANet helps in more accurate prediction of the object. This is done by concatenating the previous layers to the present layer in YOLO V4.

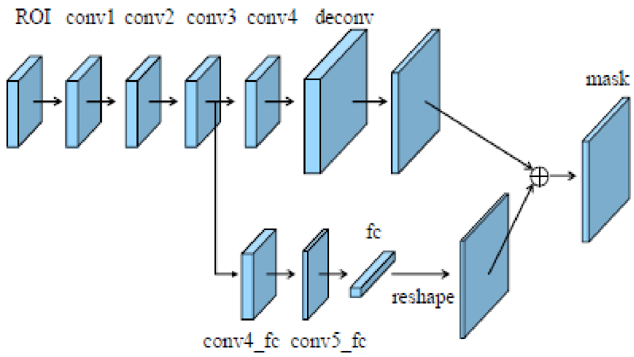


Figure 2.17 Fully Connected layer

2.4.1.3 Head/Prediction layer:

This layer performs the most important task of all the layers. It decides the class of the object detected and maps it to the class in the dataset. It is applicable for different scales of the objects and detection is made more accurate when compared to CNN. Figure 2.18 represents the head layer of YOLO V4. It is similar to the head layer of YOLO V3 and has similar functionalities. Number of channels in this layer is 225 and i.e., it can have 225 bias segments and can classify up to 255 classes.

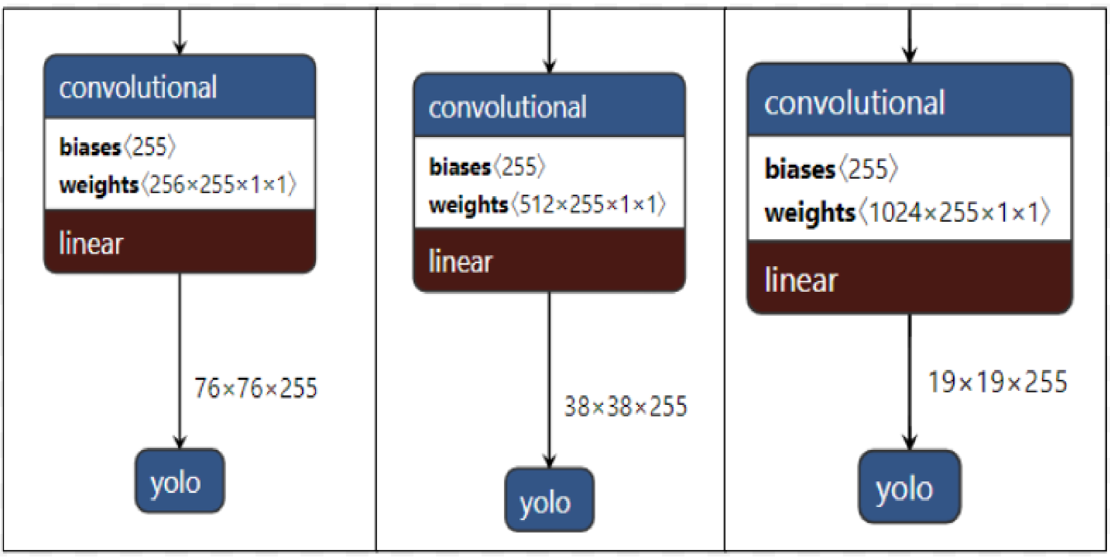


Figure 2.18 Head Layer of YOLO V4

2.4.1.4 Activation function of YOLO V4 algorithm

YOLO V4 algorithm uses Mish Activation Function. This allows the better performance of the prediction as well as smooth information processing. It enhances the training stability and increases the accuracy by 1-2.8% on the average. It is the new state of art function which is considered to be the successor to ReLU layer in CNN. Its function is given by:

$$f(x) = x\,tanh(\mathrm{Ln}(1 + e^{x})) \tag{7}$$

Where f(x) represents mish activation function and x represents the value of the detection / prediction value. Figure 2.19 shows the graph of Mish Activation function.

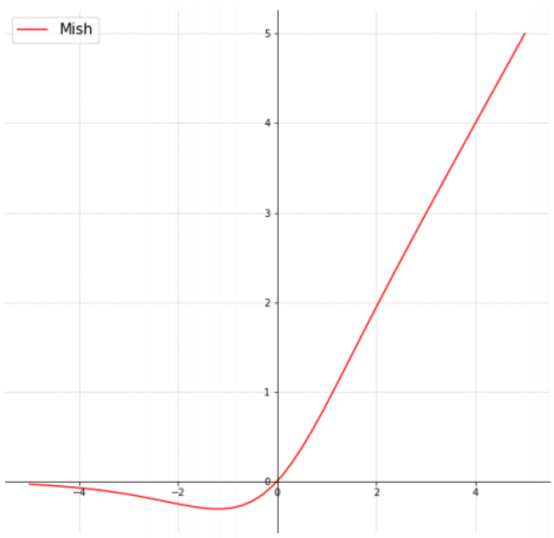


Figure 2.19 Mish Activation Graph

The Mish Activation function satisfies the condition for the ideal activation function that delivers smooth functioning and handles the negatives efficiently to deliver a wide suite for initial testing of the data.

Chapter 3

Design and Development

In this chapter, the design and development of the prototype is discussed. The prototype is designed using EagleCAD software and obstacle detection is done using YOLO V4 algorithm in Python. The whole workflow can be divided into three major section – obstacle detection algorithm, Transmission of data and reception of data. The working of the prototype is according to the pseudo codes below. Pseudocode 1 represents the code for detection algorithm. The YOLO V4 algorithm is used for detection of obstacles on the road.

Pseudocode 1: Obstacle detection algorithm

1. **Get live video feed from the camera.**
2. **Convert the video to different frames.**
3. **Determine the requires FPS for the detection.**
4. **Perform pre-processing and feature extraction.**
5. **Create YOLO V4 network using configuration required**
6. **Create Classes using Class names and wights in the COCO.names dataset.**
7. **Input the outputs of 4 and 5 to the YOLO V4 network.**
8. **Check for matching weights and features.**
9. **If a match is found:**

- **get the index**
- **perform non-maximal suppression to eliminate false positives,**
- **label with class names and confidences**
- **finally write onto serial port for transmission.**

10. **If match is not found, repeat from step 5.**
11. **Repeat from step 7 till specified time till character key ESC is pressed.**
12. **Send the detected obstacle to serial port for transmission.**

Pseudocode 2 represents the transmission of the detected data through the serial port of Arduino Nano. The timing is set for each and every obstacle for the blinking od LED so that the obstacles which are to be transmitted are easily distinguished among one another.

Pseudocode 2: Transmission of data

---

1. **Get obstacle name as serial input to transmitter.**
2. **Compare with the obstacle variable.**
3. **Set delay accordingly for the ON-state of the LED.**
   - **Car = 5s**
   - **Person = 7s**
   - **Motorbike = 10s**
   - **Truck = 12s**
   - **Bus = 15s**
4. **Turn the LED OFF.**

Pseudocode 3 represents the reception of the detected data through the serial port of Arduino Nano. Depending on the timing is set for each and every obstacle for the blinking od LED, the obstacles which are to be transmitted are detected and mapped to the respective names. The received data is displayed on the LCD screen as an indicator.

Pseudocode 3: Reception of data

---

1. **Measure the amount of time for which the photosensor senses the light.**
2. **Map the time to respective obstacle.**
   - **LED ON = 5s => Car**
   - **LED ON = 7s => Person**
   - **LED ON = 10s =>Motorbike**
   - **LED ON = 12s =>Truck**
   - **LED ON = 15s =>Bus**
3. **Display on the display device as an indication**.

With respect to the above pseudo code, the below sections dela with the design and development of the project.

3.1 Basic Workflow of the project transmitter

The basic idea of the project is to indicate the driver and drivers in the proximity of the transmitting car(transmitter) about the probability of accidents, obstacles or congestion on the road hence preventing the mishaps. The basic flow for the transmitter section is as shown in the figure 3.1.

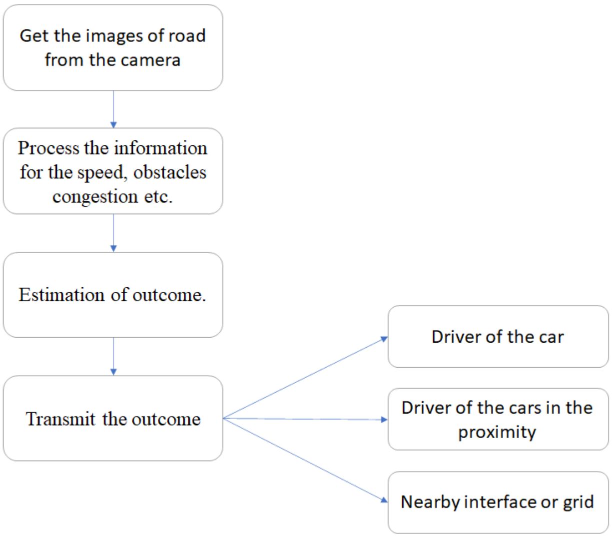


Figure 3.1 The basic flow for the transmitter section.

A camera is fit onto a car which captures the live video of the road. The captured video is processed to detect the obstacles on the road like- Speed Breakers, Humps, Animals and most importantly other vehicles. The processed data is then used to estimate the outcome mainly the speed of the vehicle, if the situation leads to an accident or not, basically estimating the road safety. The estimated output is transmitted through a visible light communication link. Using the data received by the vehicles and vehicles in the proximity of the transmitting vehicle, the required action can be taken.

3.2 Working of CNN Detection Algorithm.

The below flowchart in figure 4.2 represents the working of a detection algorithm. The video is read from the camera and is processed to detect the cars.

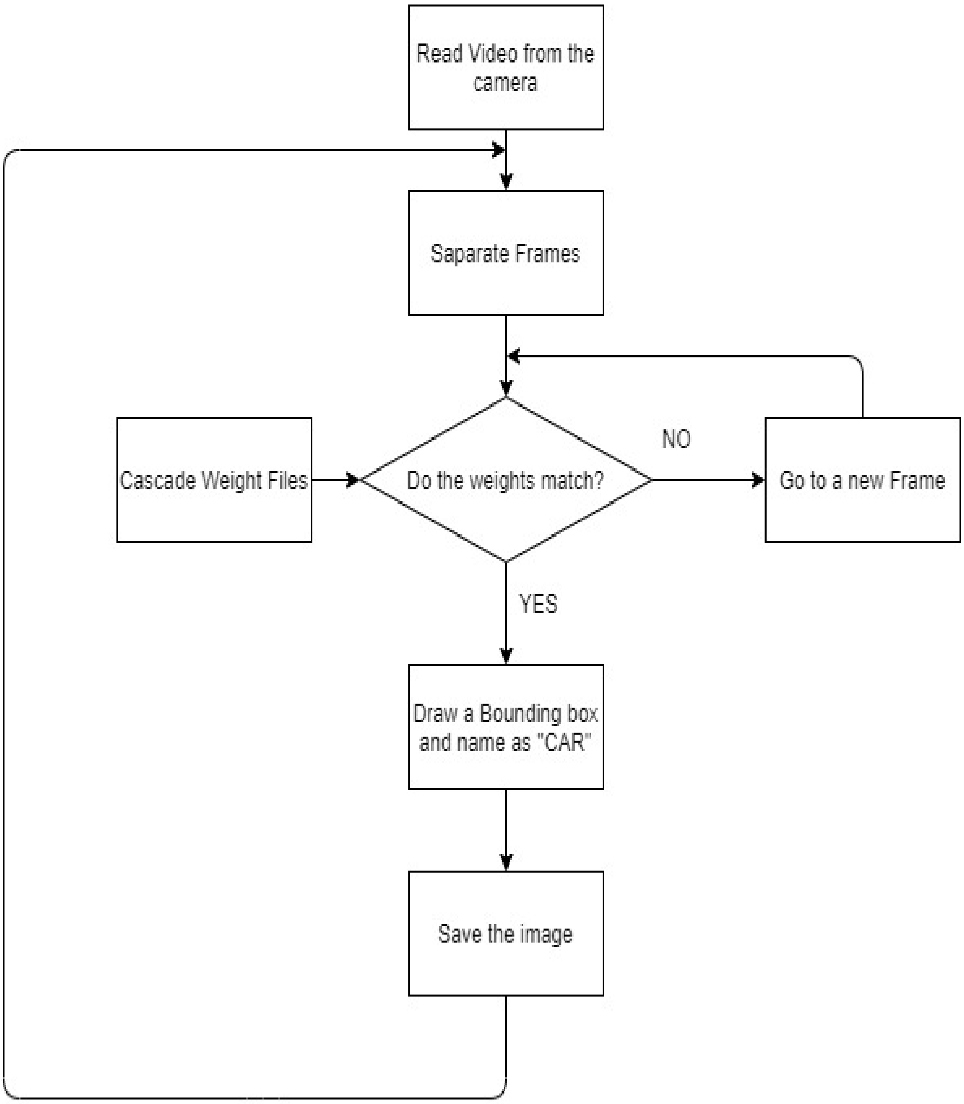


Figure 3.2 Working of CNN Detection Algorithm

The read video is divided into continuous frames and the frames are separated. The frames are then compared with the Cascade weights of car classifier. If the weights match, then a bounding box is drawn around the car. If the weights do not match a new frame is selected and the procedure is repeated.

3.3 Working of YOLO Algorithm

The working of YOLO Algorithm can be segmented into three sections. Each section has its own importance and significance. Section 1: creation of YOLO Network. Section 2: converting COCO.names to list of classes. Section 3: the use of algorithm. Figures 3.3a, 3.3b, 3.3c represent Section 1, Section 2, Section 3 respectively.

3.3.1 Section 1: Definition of YOLO Network

Creating YOLO network is one of the important steps in implementing YOLO algorithm. YOLO network comprises of the implementation of weights and network configuration in a Learning algorithm. The project is implemented using YOLO Version 4, hence the configuration and weights for the same version is used. Using mismatched weights and configuration will yield in errors and training of the algorithm is not possible. The network is created using readNet () function in python. Figure 3.3a represents the basic flow of the YOLO V4 network Creation.

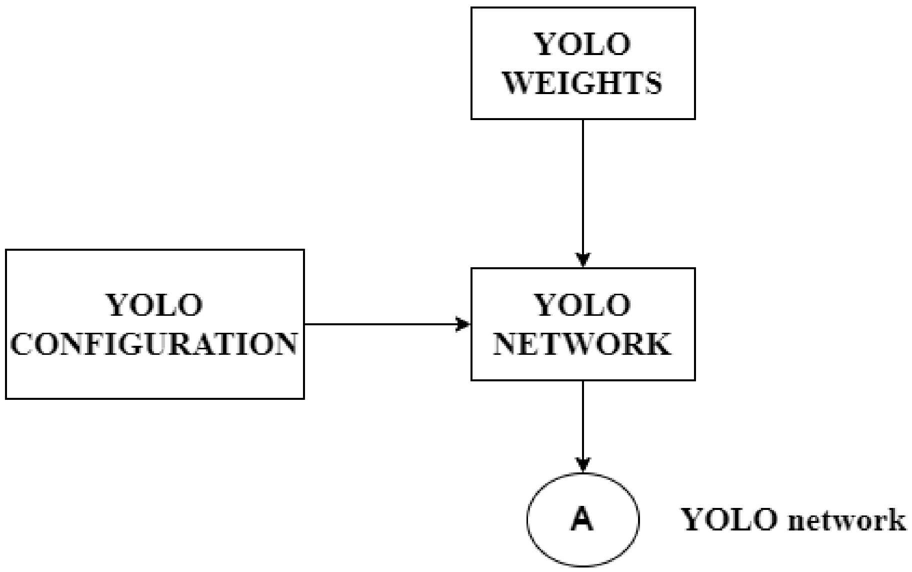


Figure 3.3a YOLO V4 Network Creation.

3.3.2 Section 2: Creating List of Classes

YOLO algorithm uses COCO.names for the classes. It is a string file which consists of all the names used by YOLO V4 algorithm as classes for classification. The names in COCO.names is stripped into a list of classes. Each class is assigned layers and output layers is determined. Figure 3.3b represents the creation of the class list in accessible format.

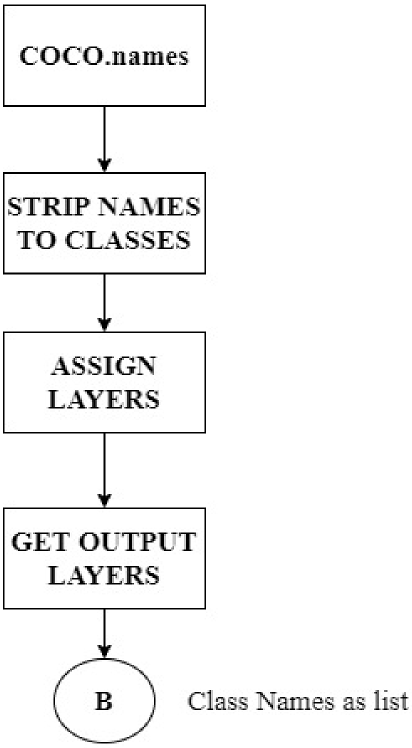


Figure 3.3b Creating list of classes

3.3.3 Section 3: Use of YOLO Algorithm in the Obstacle detection

YOLO Algorithm is state of the art algorithm for real time object detection. It has accuracy percentage of about 90% depending on the object placement to the camera and has a smaller number of false positives that are detected. The YOLO algorithm used in the project is YOLO V4 algorithm and is most flexible and accurate compared to other algorithms. It takes in real time video input for the processing.

The input given to the algorithm is real time video of the road. The inputted video is converted into images and pre-processing and feature extraction is performed in the converted images. These images are then input to the YOLO network as discussed in 3.3.1. And also, the classes as discussed in 3.3.2 is inputted to the network. If the match of the object and the class is found, the index of the class is considered, the false positive detection is eliminated and then the bounding box is inserted around the object labelling it with the class name and confidence. If the match is not found, the YOLO network tries to find match for the next incoming image.

Figure 3.3c represents the YOLO algorithm used in the project. The classes used for detection are – Car, Motorbike, Person, Bus, Truck, Traffic Signal.

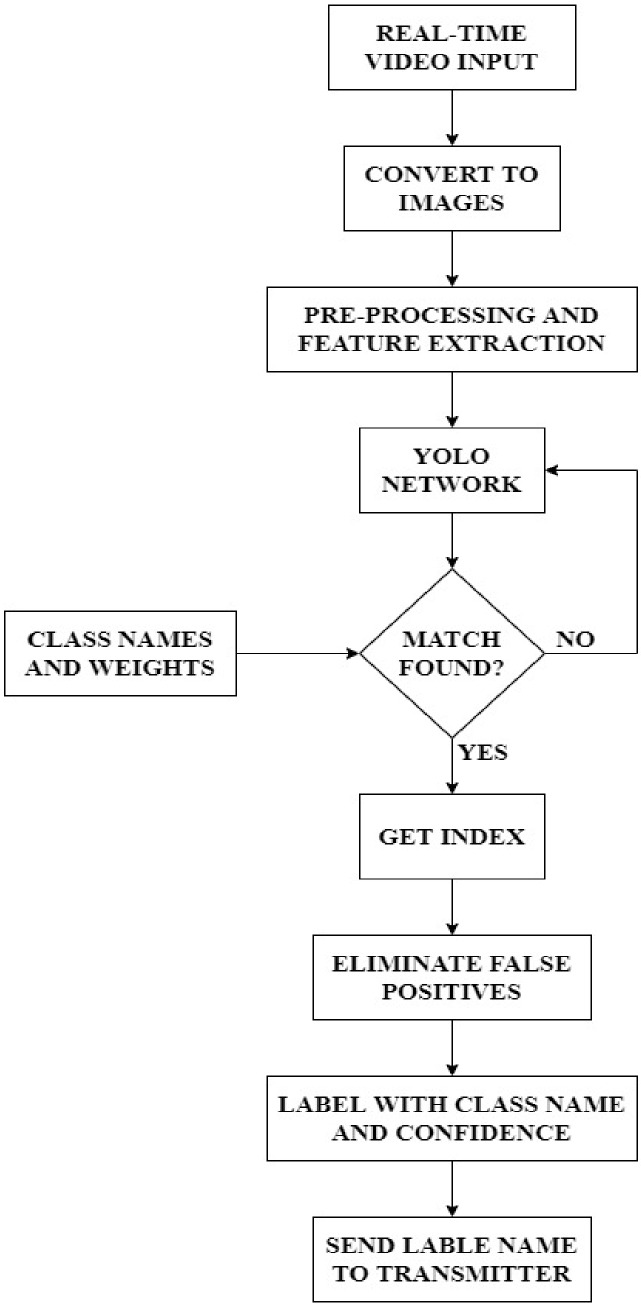


Figure 3.3c Use of YOLO Algorithm in the Obstacle detection

3.4 Working of VLC Transmitter

VLC transmitter sends the user information in the form of light pulses. These pulses carry information about the obstacles on the road especially - car, motorbike, person, bus, truck, traffic signal. This information is obtained as a string of characters and light is transmitted according to the string obtained.

The data obtained from the detection algorithm, i.e., the obstacles is converted to binary. The On-Off Keying (OOK) modulation is performed in the string obtained and this OOK drives the LED. The output obtained is the light which carries the information. Figure 3.4 represents the working flow of the VLC Transmitter.

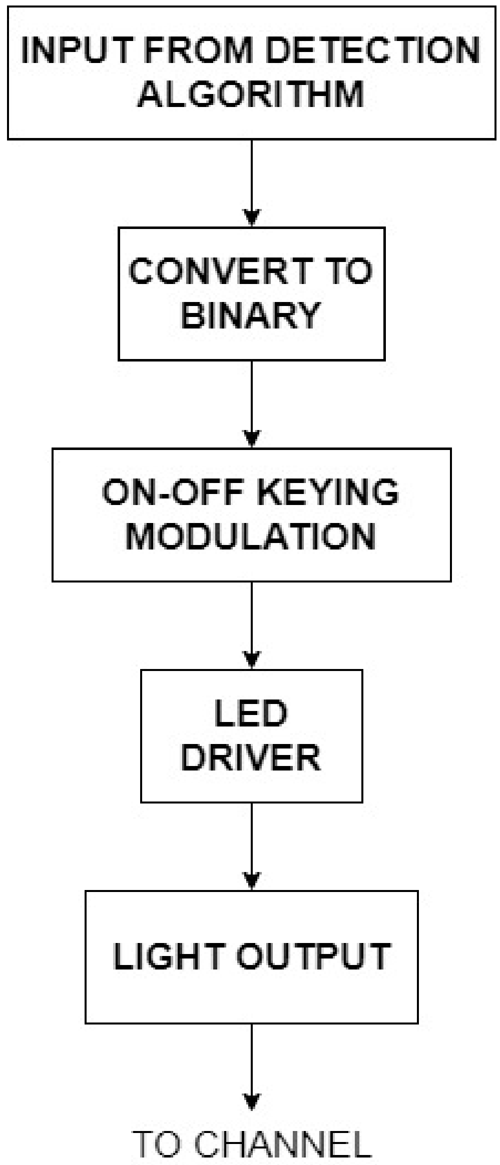


Figure 3.4 Work Flow of VLC Transmitter

3.5 Working of VLC Receiver

The light input received from the transmitter is detected using the photo detector – light dependent resistor. The received output from the LDR undergoes OOK demodulation. Since the obtained output may be weak, it is amplified. The amplified output is then converted into the original data using a DAC. The obtained DAC output is the obstacle that is present on the road. This is displayed on the screen or using LDC display. Figure 3.5 represents the work flow of the VLC Receiver.

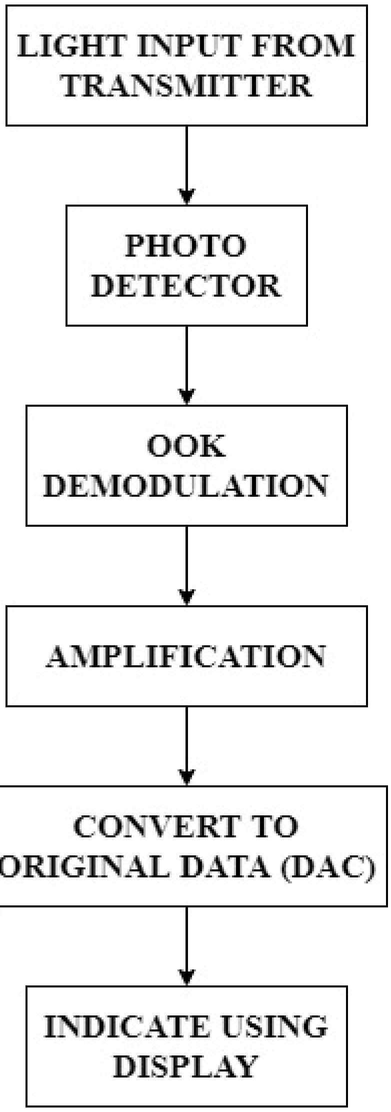


Figure 3.5 Work flow of the VLC Receiver

3.6 Hardware components

The hardware components required for the conduction of the thesis is as follows.

- LiFi Module
- Arduino Nano - atmega328p
- LED – White colour (other colours can also be used as to test the prototype)
- LCD display – 16X2 LDC display to display the message sent by Transmitter.
- LCD Driver
- LDR – Light Dependent Resistor
- Connecting Wires

- PCB Board
- Hot glue kit

3.6.1 Hardware Design

3.6.1.1 Transmitter

The hardware connections for the transmitter are as shown in the figure 3.6a. The Arduino Nano is coded for modulation schemes. The LED is connected to Digital Pin 8 and is connected as output terminal. Figure 3.6b represents the Hardware Connected on a PCB Board. Figure 3.6c represents the transmitter photo.

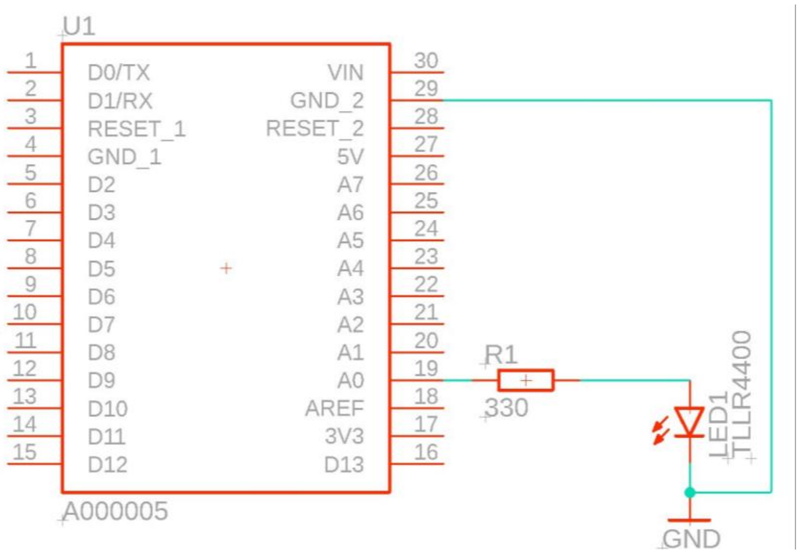


Figure 3.6 (a) Circuit Diagram of Transmitter

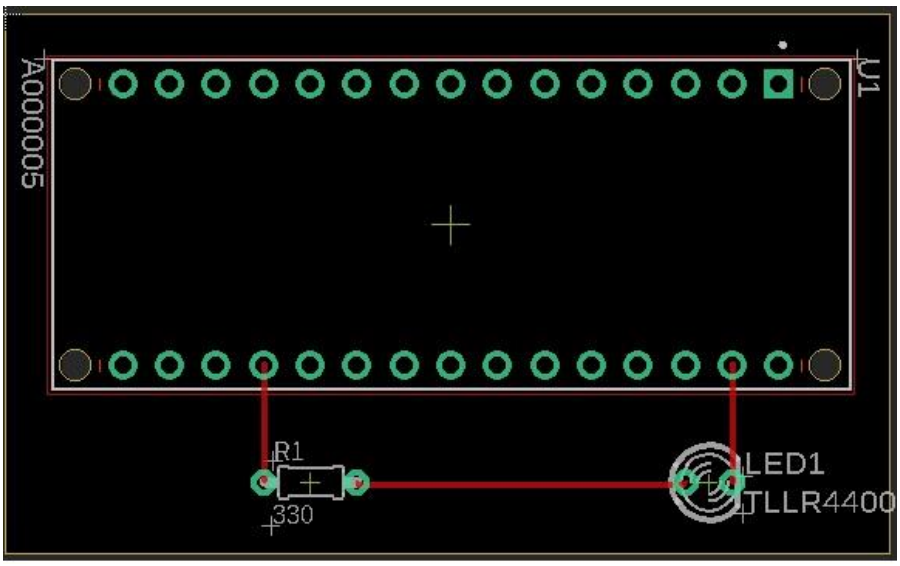


Figure 3.6(b) Board Diagram Of transmitter

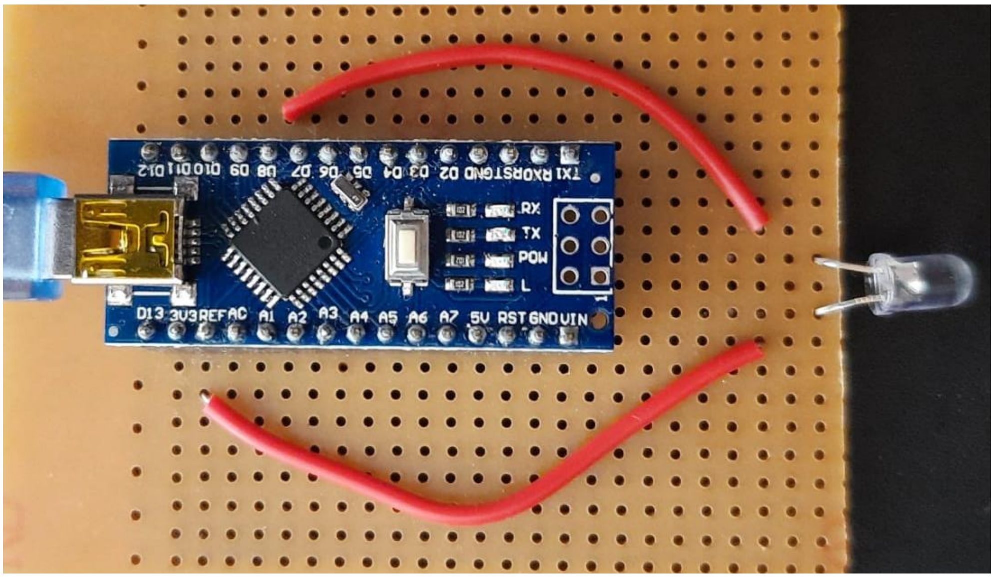


Figure 3.6 (c) Transmitter

3.6.1.2 Receiver

The hardware connections for the receiver are as shown in the figure 3.7a. The Arduino Nano is coded for modulation schemes. The LDR is connected to Digital Pin 8 and is connected as output terminal. The output obtained after the processing is displayed on the LCD using LCD driver. LED2 is used as indication device, instead of LED2, a 16X2 LCD display is used. Figure 3.7b represents the Hardware Connected on a PCB Board. Figure 3.7c represents the receiver photo.

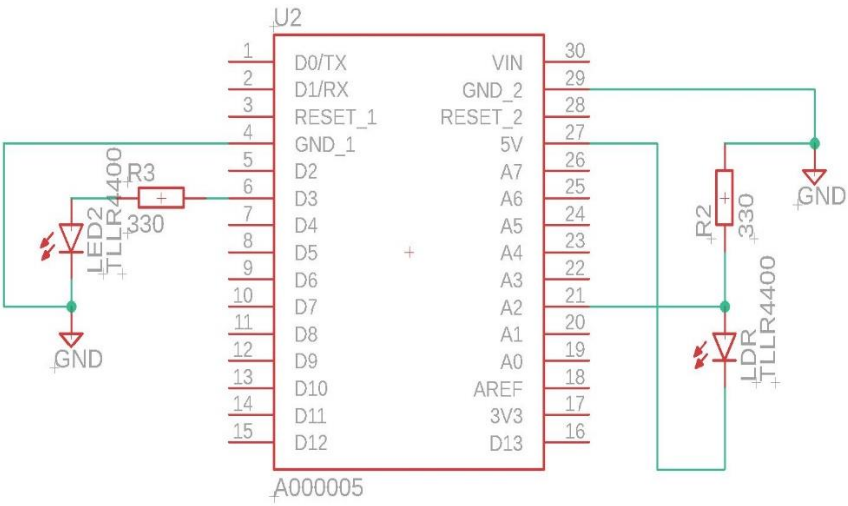


Figure 3.7 (a) Circuit diagram of receiver

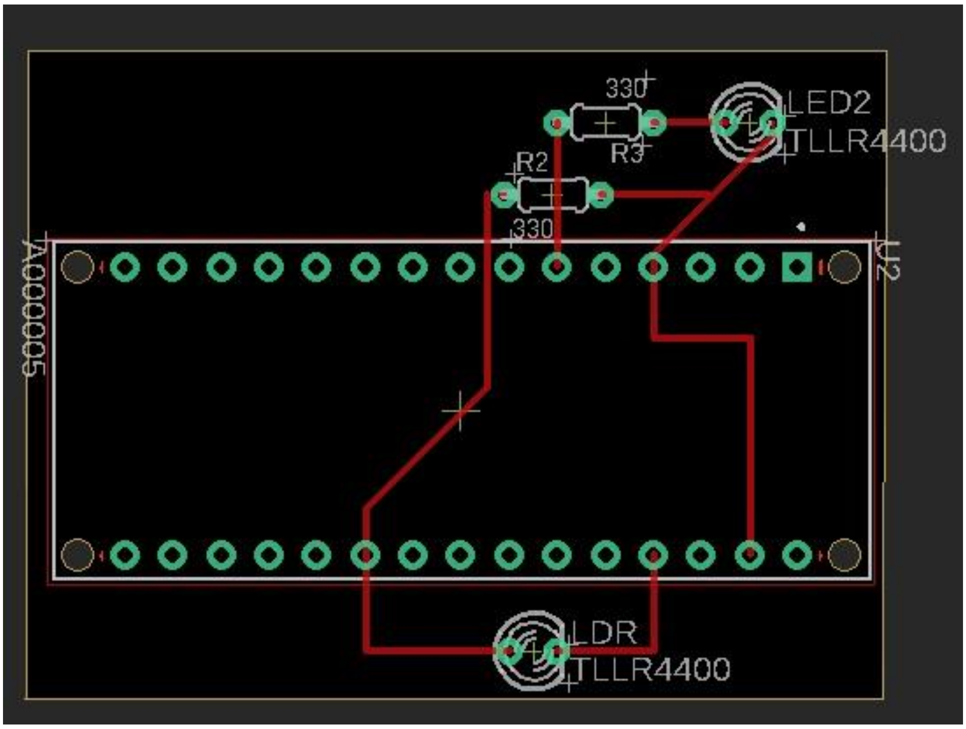


Figure 3.7 (b) Board diagram of receiver

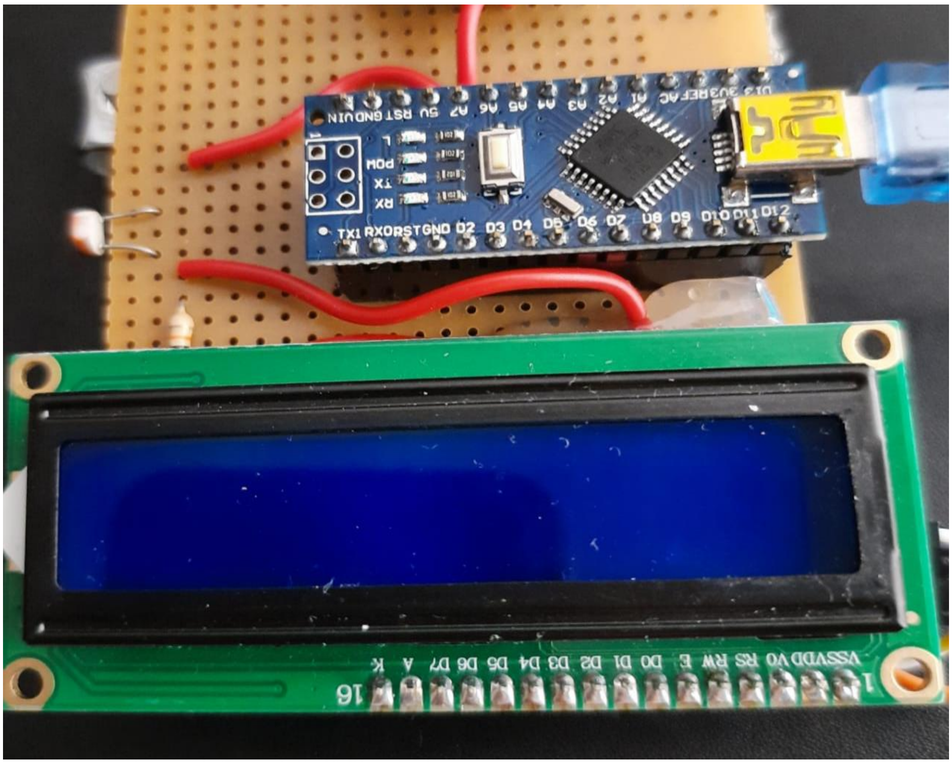


Figure 3.7 (c) Receiver

s

3.7 Software Components

- Python version 4 for YOLO V4 programming. This is used for obstacle detection.
    - Libraires used include: OpenCV, NumPy, PySerial, OS, time, CVZone.

    These libraries include various functions for the detection algorithm to perform at its maximum yielding greater efficiency at less amount of time.

- Arduino IDE for coding of transmitter and receiver.
- EagleCAD for designing and simulations.

Chapter 4

Results and Observations

In this section, we will go through the different results obtained at different sections of the project.

4.1 Results Obtained

4.1.1 Results of CNN Algorithm

An algorithm to detect the Cars on the road was successfully run using Python. This algorithm mainly uses OpenCV and NumPy packages to detect the vehicles. Two video datasets were tested and the results are as shown in figures 4.1a and 4.1b.

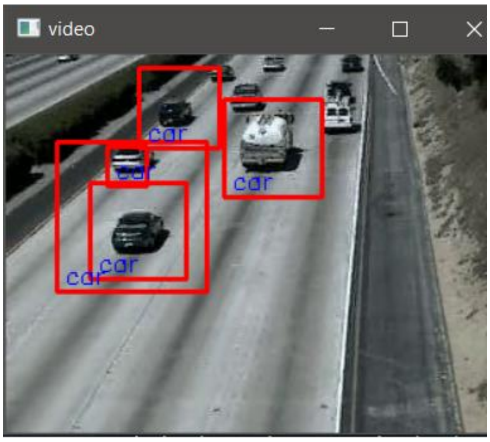


Figure 4.1 (a) Detection of Cars- one way detection

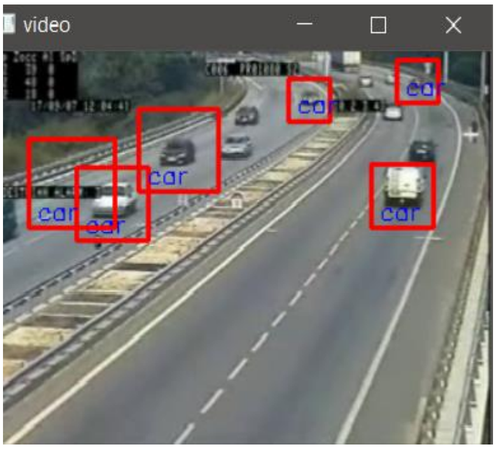


Figure 4.1 (b) Detection of cars in a two-way lane

4.1.2 Results of yolo Algorithm

The YOLO algorithm uses the OpenCV, NumPy and Time packages to detect and verify the obstacles in the video. There were three datasets used and the results are shown in the figures 4.2a-4.2c. The accuracy of the algorithm is greater than 80%. The datasets were collected from different sources. Dataset 1 was collected from a travel log at Hosakote toll, Karnataka. Dataset 2 was taken at NH-7, Yelahanka, Bangalore. Dataset 3 was collected at from a travel log from Kerala to Bangalore. All the datasets were trimmed for a length of 1 minute and 30 seconds for the recognition of the obstacles on the road. The output of the YOLO Algorithm is shown below.

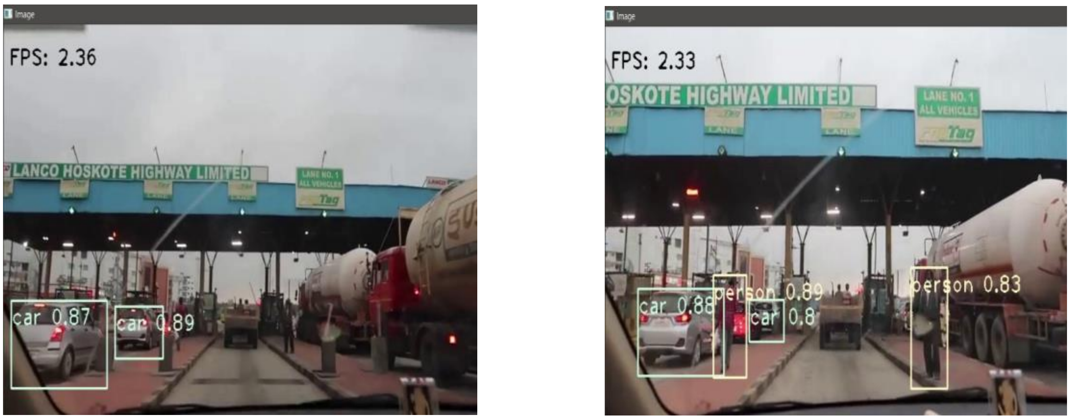


Figure 4.2 (a) Outputs of YOLO V4 algorithm on Dataset 1

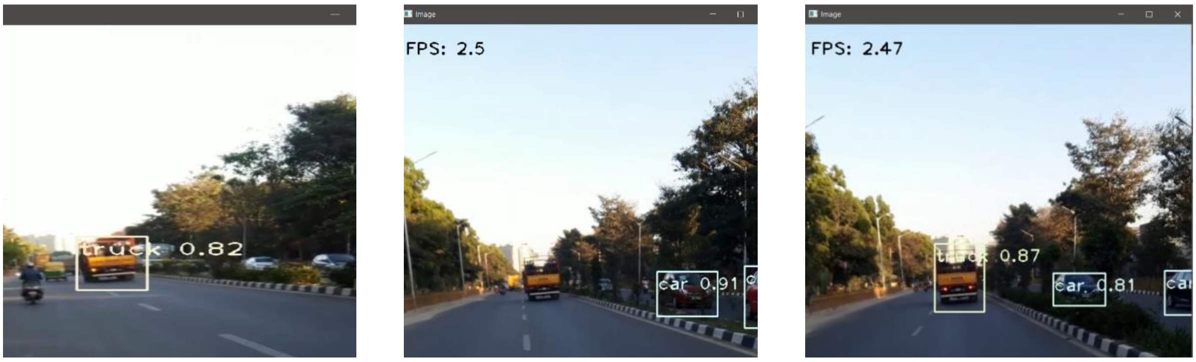


Figure 4.2 (b) Outputs of YOLO V4 algorithm on Dataset 2

Figure 4.2 (c) Outputs of YOLO V4 algorithm on Dataset 3

4.1.3 Output at the LiFi Transmitter and Receiver

The various scenarios were tested out for obstacles and the obstacles were fed to the LiFi transmitter. The LiFi transmitter is connected to COM5 of the computer and LiFi receiver is connected to COM3. The delay in the outputs is as shown in the figure 4.3a and 4.3b.

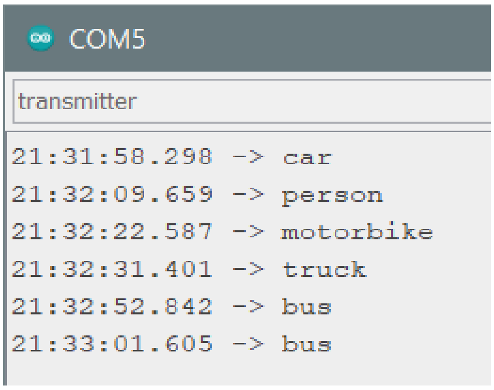


Figure 4.3 (a) LiFi Transmitter

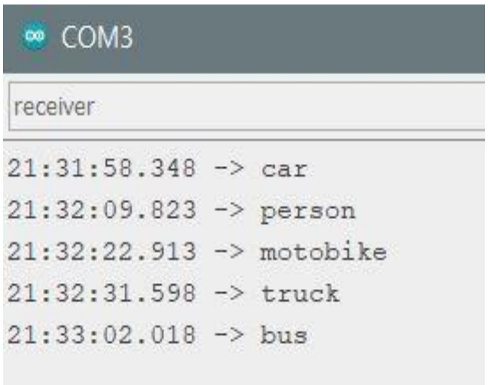


Figure 4.3 (b) LiFi Receiver

Figures 4.3c-4.3g represents the output obtained on the LCD Display after transmission.

Figure 4.3 (c) Output at LCD display when ‘car’ is transmitted

Figure 4.3 (d) Output at LCD display when ‘person’ is transmitted

Figure 4.3 (e) Output at LCD display when 'motorbike' is transmitted

Figure 4.3 (f) Output at LCD display when 'truck' is transmitted

Figure 4.3 (g) Output at LCD display when 'bus' is transmitted

During the communication, the distance between the transmitter and receiver is 30cm or 1 foot. This distance can be improved by using LASER for light transmission instead of LED. Whenever there is an obstruction to communication, the communication link is broken due to opacity of the object. Hence the communication link is supposed to be free from obstacles.

4.2 Observations

4.2.1 CNN algorithm

CNN algorithm using Cascade Classifier when executed for the object detection showed a lot of false positives. Hence in order to reduce the number of false positives, a lot of changes needed to be and the efficiency of the algorithm was found to be very less. The algorithm was not able to detect objects in dim lighting because the feature extraction would be a problem. In order to overcome these drawbacks, YOLO algorithm was used.

4.2.2 YOLO Algorithm

When using YOLO Algorithm, a set of certain system specifications are to be met. In the systems where these specifications are not met, it is not feasible to execute this algorithm as it may crash the system. Though the algorithm can detect the obstacles in dim lights, it cannot detect the obstacles in the dark. This may be due to the no background light which makes it impossible for feature extraction and also interference due to high beam lights which blind the camera because of very high intensity light. The algorithm also fails at higher FPS for more accurate detection of objects. This is due to the fact that it is very difficult to determine the Non-Maximal Suppression ratio at higher FPS.

4.2.3 V2V communication System

It is observed that the proposed V2V System is highly directional. I.e., the photo sensor is to be aligned with the LED in a single line. The reception is not possible if they are not in the same line. The automation of the serial writing of the transmitted string is difficult as the python is not compatible with Arduino but by using some libraries it can be achieved. The range of the proposed system is very short and it can be extended by using mirroring techniques as well as high power LED to transmit data. Since the transmission and reception is highly directional, laser can also be used in place of LED. This will yield in higher accuracy and less latency when compared to LED.

4.3 Calculation of Throughput and Delay

The throughput of the system is the ratio of the number of messages received correctly to the total number of messages sent. It can be written as –

$$Throughput = \frac{Number\ of\ messages\ received}{Total\ number\ of\ messages\ sent}$$

Factors affecting the throughput include the distance between the transmitter and receiver, the alignment of the transmitter and receiver. Smaller the distance, greater is the throughput. It can be concluded that the transmitter and receiver setup is highly directional, i.e., the LED and the Photo-Sensor are to be properly aligned so that the received data is of less erroneous.

As shown in the figures, 4.3a and 4.3b, the total number of messages sent is 6 and total received is 5. This indicates the throughput is 5/6 = 83.3333% at a distance of 30cm.

The delay is the time difference between the transmission time and received time. Lesser is the delay, more efficient the system will be.

$$Delay = Reception\ time - Transmission\ time$$

The factors that affect the delay are the distance between the transmitter and receiver, the colour of the light used. Tables 4.1 represent the delay calculations. The calculations are done as per the results obtained in figures 4.3a and 4.3b.

Table 4.1 Delay calculations

Transmission time (HH:MM: SS.ms)	**Reception Time (HH:MM: SS.ms)**	**Delay (ms)**
21:31:58.298	21:31:58.348	0.05
21:32:09.659	21:32:09.823	0.164
21:32:22.587	21:32:22.913	0.326
21:32:37.401	21:32:31.598	0.197
21:33:01.605	21:33:02.018	0.413

The average delay is found to be 0.23ms.

Chapter 5

Conclusion and Future Scope

5.1 Conclusion

The Vehicular communication is one of the most required system in the present age scenario. It helps in better road performance of a given vehicle when it comes in terms of the user end applications. The vehicular systems implemented presently is based on ZigBee and RF communications which is comparatively costlier and very difficult for replacement. Hence the use of VLC where the lights present in the car or vehicle can be used for transmission and the receiver is to be employed in the vehicles which are near proximity.

Since the use of VLC is in extensive research, an application of the domain in vehicular communication is most feasible since it is DSRC. The proposed system in the thesis is uses the YOLO algorithm for the object detection and a simple hardware for VLC. The system is found to have accuracy greater than 80% in object detection and communication throughput. The delay between the transmitter and receiver is as shown in table 4.1. Hence this system can be a basic prototype for the visible light vehicular communications.

The usage of VLC system for vehicular communication has major advantages and can be most effective when compared to present RF technology systems. It can be concluded that the VLC uses unlicensed band for communication. The bandwidth provided is greater when compared to existing RF technologies.

The other advantages include –

d. There is no electro-magnetic interference.
e. There is less power consumption
f. More secure due to LOS communication.
g. Less or no risk because of lesser consumption of transmission power.
h. Installation complexity is very less.
i. Power amplifier is not required.
j. DSRC for better communication with less outdoor noise considerations.

5.2 Future Scope

The Various aspects which can be further explored in the research are as follows.

- The detection algorithm for object detection in darker environment can be developed.
- The omni-directional receivers can be researched.
- The use of lights of different frequencies and wavelengths for the transmission and reception and their performance analysis can be made.
- The transmitter and receiver placement on the vehicle for better performance can be studied.
- Another detailed study for the location of camera can be made with respect to different vehicles in picture.
- The issue of range and its extension by techniques can be researched.

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