Neural Network and Internet of Things Implementation to aid Pedestrian Safety

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Abstract

Increasing Pedestrian Safety is currently an issue that most countries are facing as pedestrian security is of prime concern. This paper aims to propose a technique that utilizes the camera data collected for each street by Montreal's government. The collected data is used to train a neural network using simulation and TensorFlow, which then identifies pedestrian patterns that are observed during each time of the day. These patterns can then aid in enhancing pedestrian security measures in the chosen streets. The neural network is trained to identify the number of pedestrians in the streets, peak hours at which pedestrian density is maximum, streets which have most pedestrian density throughout the day, and various other patterns described in this work. This data is then used to control the Pedestrian and traffic lights, issue warnings onto the pedestrians' smartphones in the vicinity of the risk area etc. This task is achieved by utilizing Internet of Things (IoT), Cloud Services, and micro-controllers installed near street lights on streets. Thus, this work not only promotes pedestrian safety but also acts as an aid to developing Smart Cities. This work makes use of the image data freely provided by the city of Montreal. It also discusses the advantages, weaknesses, limitations, and future scope of the above-mentioned proposed technique.

Keywords
Internet of Things, Pedestrian safety, Convoluted Neural Network, Cloud services, Micro-controllers

1. Introduction

The ongoing constructions in the city of Montreal have affected the traffic control systems and made the pedestrians more vulnerable to accidents, and other security threats. This requires an urgent traffic management system which is sustainable, efficient, and multicriteria based, and can ensure pedestrian security in any circumstance.

This paper aims to present such a solution which incorporates technologies such as Internet of Things (IoT), neural networks, simulation and modeling, and Cloud services. It provides a framework that allows the detection of pedestrian patterns during peak, as well as non-peak hours, which can in turn be incorporated to manage the traffic system efficiently while ensuring the security of pedestrians. The proposed technique involves using the data collected from monitoring cameras installed by the city government in all major streets of the city. The images collected by these cameras are freely available for usage. The city currently does not incorporate this data into any smart traffic management systems, instead this data is only analyzed during emergency situations.

The framework provided in this paper, aims to collect this data and use it to train the convolutional neural network to identify pedestrian patterns, which can in turn provide insights into enhancing pedestrian security.

Various implementation methodologies have been implemented in recent past and turned out to be a failure. Several aspects like cultural, economic and psychological affect the growth of the city on its own. These factors are widely influencing the production and betterment of the current situation of the city. The main issue that needs to be resolved when we talk about pedestrian safety is, we can save pedestrians or just reduce the risks. Thus, a system assuring pedestrian safety needs to be well analyzed and well versed.

The technologies that have aided in developing this framework are as follows:

The Machine learning applications such as neural networks can be used by the free and open source math library called Tensor Flow. It provides excellent functionalities and services when compared to any other machine learning framework. Mainly used for understanding, classification, creation, prediction and discovering. TensorFlow applications can run on cloud clusters, IOS, androids and various CPU's and GPU's. It gives an ideal representation with the data flow graphs and numerical and mathematical expressions.

TensorFlow helps computers to verify every single data and identify what it represents and its learning patterns. A most common output of machine learning is to identify what an image represents. During the training of the dataset, an image classification model is fed images and their associated labels. Each label is the name of a distinct concept, or class, that the model will learn to recognize. Given enough training data (thousands of images per label), an image classification model can learn to predict whether new images belong to any of the classes it has been trained on. This process is called inference. To perform inference, an image is passed as input into a model. The model will then output an array of probabilities between 0 & 1.

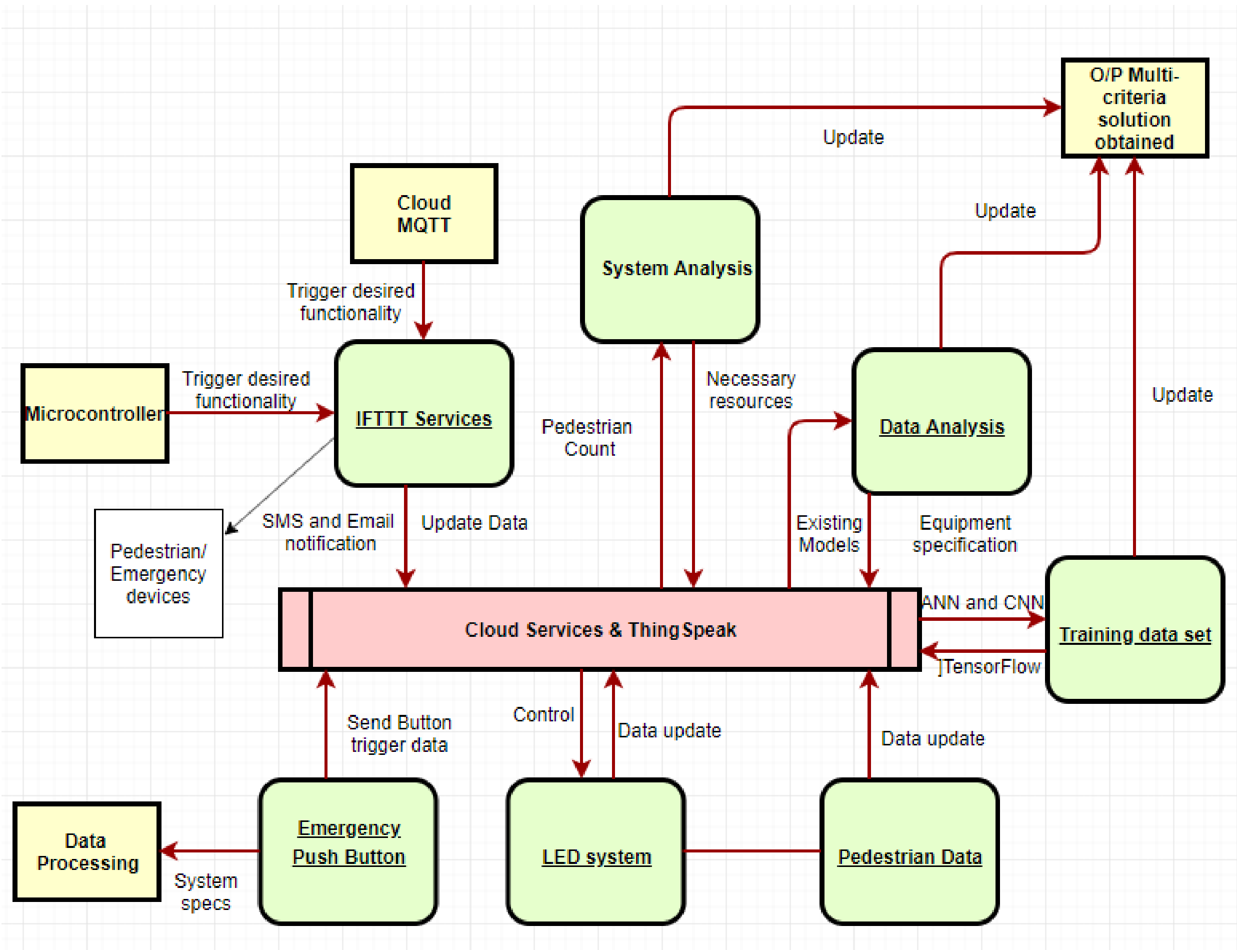


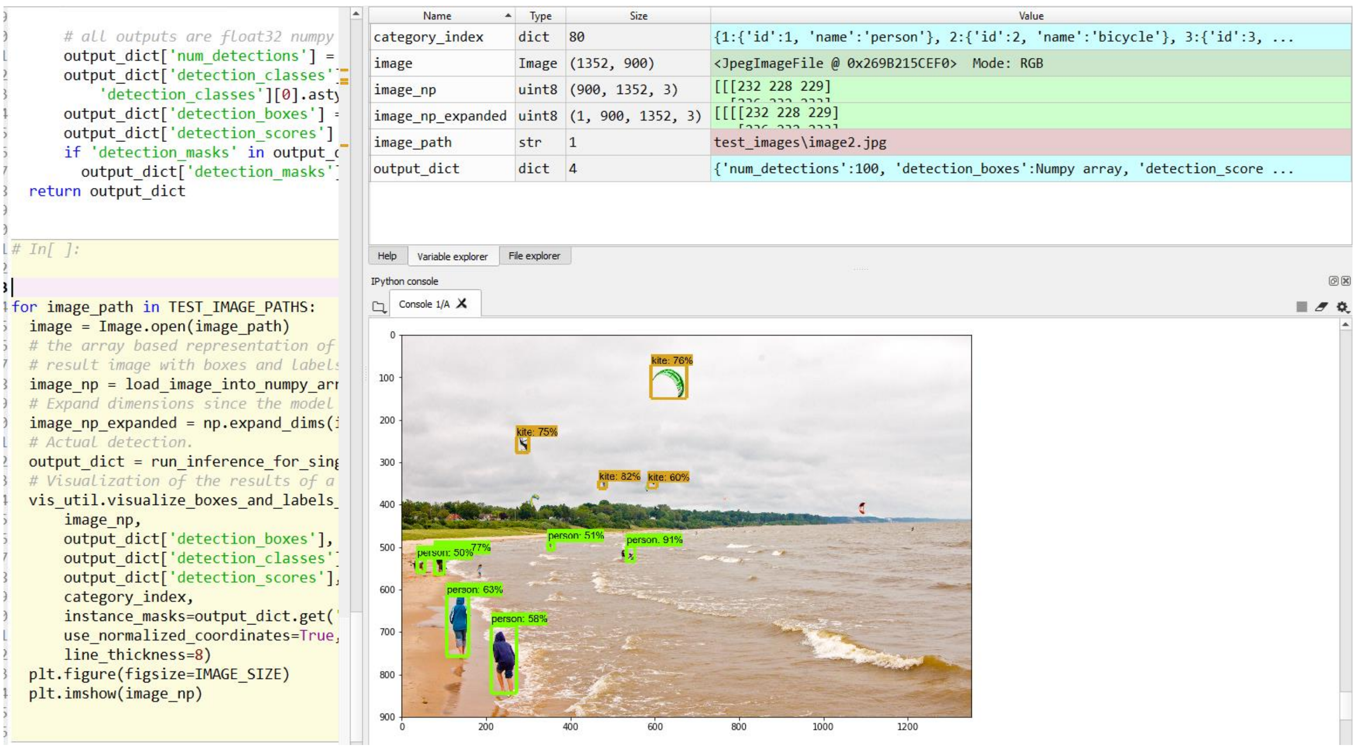
Figure 1. Flowchart for flow of data amongst the various components involved in the system

1.2 Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN)

To train a complicated data set of the pedestrians at the intersections ANN computing system which act like an animal brain, such systems act by understanding examples rather than coding them explicitly.

For interpreting and analyzing visual imagery ConvNet with multilayer perception inspired by biological processes where the neurons resemble the organization of the animal visual cortex. Data pre-processing for the convolutional neural networks combining videos over longer periods. The API was trained on COCO dataset (Common objects in context). A data set of 100K images for pedestrians were collected across an intersection out of which 3000 were trained. A selection of trainable detection models like: Single shot Multi Box detector (SSD) with MobileNet, SSD with Inception V2, Region Based Fully Convolutional Networks (R-FCN) with Resnet 101, Faster RCNN with resnet 101, Faster RCNN with inception Resnet V2. Various libraries like Protobuf 2.6, Pillow 1.0, lxml, tf slim, Jupyter notebook, Matplotlib and TesnorFlow. After training the dataset we can obtain an accuracy of 98% can be obtained for the pedestrian detection.

Figure 2. Test case for Tensor Flow object detection API



The dataset thus obtained can be used to detect the congestion at intersections across the city. The collected data is thus useful for providing information to implement the solution provided. The dataset is accurate as it is real time and is collected from a trusted source. After gathering the images from the cameras, it was processed in the form of a video. This made it easier to omit the unwanted images and calculate the density of the pedestrians across the intersections. Further, this data can be analyzed and trained to differentiate if there is a pet, male, female, young or an old person which would give us a clear idea about the target pedestrians.

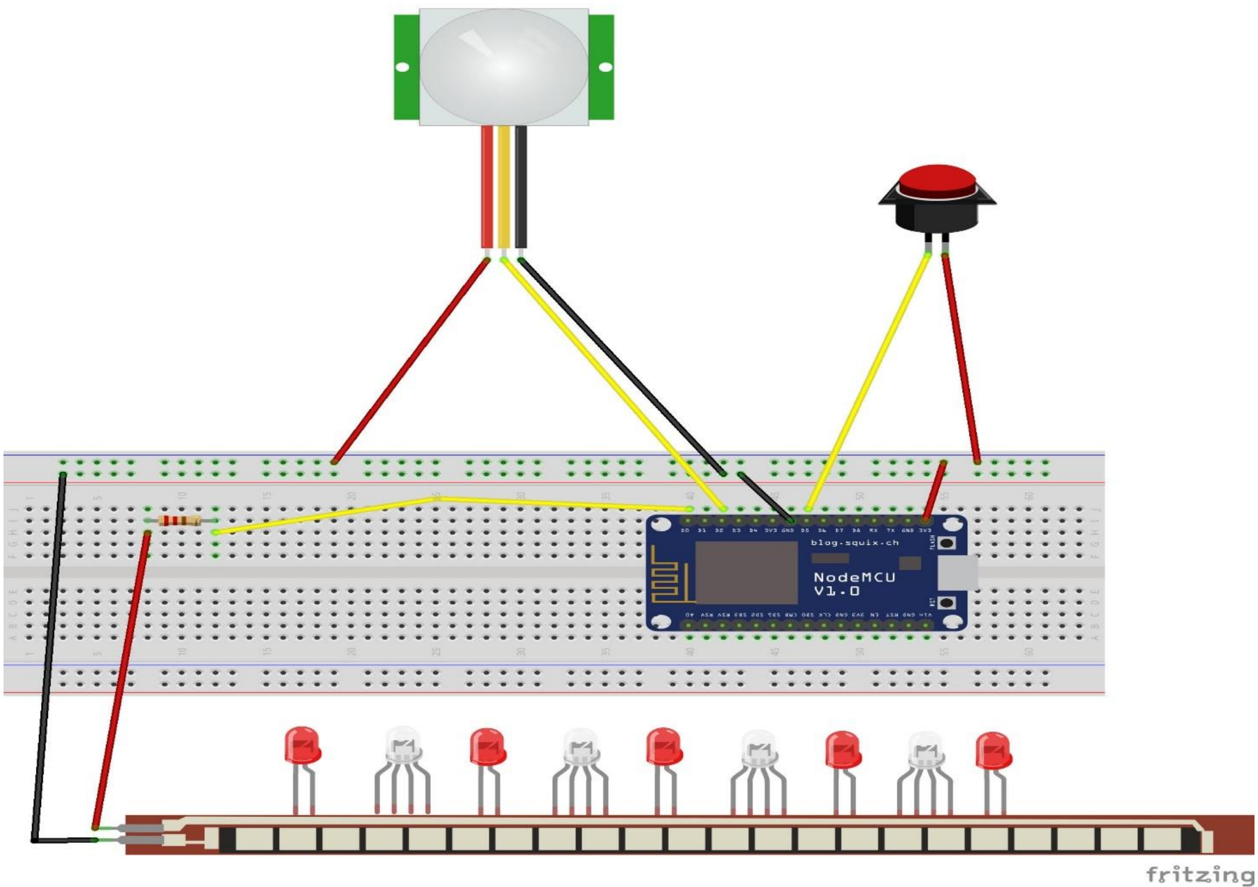
1.3 Internet of Things

Machine2Machine interaction using cloud services with the approach of a publish-subscribe model, IoT provides a solution for a smart traffic system enhancing pedestrian safety and security in the proposed system. Cloud protocol MQTT and Web-Based service IFTTT are used to send and receive the data.

Cloud MQTT protocol (Message Queuing Telemetry Transport) allows the sensed data to be sent onto the Cloud. In this framework, it would involve sending alert messages, warnings etc. to the Cloud, where this data is analyzed and further sent onto pedestrian devices, or various other smart devices as needed.

IFTTT Web services aid in the creation of custom applets that can achieve small tasks such as sending email alerts, or SMS notifications etc., based on the needs of the proposed framework.

Figure 3. Circuit showing multiple components of the Motion Sensor and Emergency Push Button



The work is further divided as follows; section 2 of this work analyzes the related works in the field of Internet of Things (IoT), and pedestrian safety. Section 3 describes the implementation methodology adopted for the proposed solution. Section 4 provides the discussion that compares and contrasts the proposed solutions with the currently existing solutions, while Section 5 concludes the work.

2. Literature Review

Year	Title	Authors	Approach/Algorithm used	Model remarks	Parameters considered	Data Set	Objective	Remarks
2015	Internet of Things for Intelligent Traffic Monitoring System:	Made Oka Widyantara, Nyoman Putra	Detecting traffic congestion	Intelligent Traffic Monitoring System (ITMS)	GPS as sensor, GPRS based data transport	Speed(Km/h)	Visualization of road desnsity category	Effective way of using GPSand web based traffic information technology
2015	Intelligent Traffic Information System Based on Integration of Internet of Things and Agent	Hasan Omar Al-Sakran	Active radio-frequency identification (RFID), wireless sensor technologies, object ad-hoc networking, and	Intelligent Traffic Information System Based on Integration of Internet of Things and Agent Technology	Interface and performance evaluation of the simulation results	Not moving vehicles, average waiting time and average of speed of the vehicles	Proposed system can provide a new way of monitoring traffic flow that helps	Proposed traffic system based on the IoT consists of a large number of RFIDs and sensors that transmit data
2018	Automated pedestrian safety analysis using data from traffic monitoring cameras	Weijia Xu, Natalia Ruiz-Juri	The video content recognition algorithm	Convert video recordings into queryable information, which can accommodate multiple subsequent use cases without re-procesing	GPUs and distributed computing clusters to enable the analysis of large data volumes	Time range, Number of files, Average size per video file	Reduce the effort involved in analyzing video data, and frameworks such as the one presented here can facilitate research traditionally based on manual video data analysis,	approach is likely to be overestimating the presence of pedestrian on the street because "person" objects are not limited to pedestrians; they also include cyclists, motorists, and drivers with open roof/windows
2016	Modelling Pedestrian Safety with respect to Road Traffic Crashes by Estimating the Safety of Paths	Charlotte Hannah , Irena Spasi´ and Padraig Corcoran	A novel linear model of pedestrian safety in urban areas that considers a single independent variable of pedestrian path safety	Model assumes that a pedestrian always follows the safest path where the safety of a path is defined as the weighted sum of its length and inherent safety.	Pavement Network Construction, Computing Edge Safety	UK cities the corresponding estimated pedestrian safety and number of pedestrian casualties per million population	a linear regression model of the estimated pedestrian safety accurately predicts the corresponding number of pedestrian casualties.	Evident from the scatter plot that the relationship between the estimated pedestrian safety and number of pedestrian casualties per million population is strongly linear
2009	Canadian Research on Pedestrian Safety	Ron Van Houten and J.E. Louis Malenfant	reports research in six areas of pedestrian safety	The overall effectiveness of pedestrian-activated flashing beacons remains to be evaluated, but it is clear that their use is associated with an increase in the percentage of motorists yielding to pedestrians	Crosswalks, LED technology	WALK interval of pedestrians	Pedestrian safety synthesis reports prepared for the Federal Highway Administration (FHWA)	Additional research needs to be conducted to determine the best way to employ pedestrianactivated signals at crosswalks
2010	In-Vehicle Intelligent Transport System for Preventing Road Accidents Using Internet of Things	Preethi Govindarajulu , Dr. P. Ezhumalai	A privacy-preserving protocol for enhancing security in vehicular crowdsensing-based road surface condition monitoring system using fog computing	The intelligent transport system using internet of things is implemented in the vehicle to provide the safe and comfortable driving for users and also provides the road safety to avoid the unnecessary accidents.	Cooperative intelligent transportation system (C-ITS), Automated guided vehicles (AVGs),	Vulnerable road users (VRU), Sensor data	Road safety is the prevention and protection of human lives from road accidents by implementing road safety measures.	The efficient distribution of intelligent transport system (ITS) messages is fundamental for the deployment and acceptance of ITS applications by mobile network operators and the automotive industry
2018	An IoT Architecture for Assessing Road Safety in Smart Cities	Abd-Elhamid M. Taha	Wireless Communications and Mobile Computing	HMM using Matlab as per thedescription , mapped the state of safety to the edge weights in the County road network.	PostgreSQL built on a Red Hat EnterpriseLinux Developer OS, Probabilistic models, HMM	NYC OpenData collisions dataset, as detailed in [□□]speci□es collision date, time, longitude, latitude, and address(street and/or intersection). dataset also qualifes colli-sions based on deaths and injuries for motorists, pedestrians,and cyclists, as well as other contributing factors and vehicletypes	Viability of an economic road safetymonitoring and assessment solution through exploitingadvances in the Internet of □ings (IoT)	A closer categorization of collision might be needed a□erisolating weekdays from weekends. Notwithstanding, thechoice of windows does not result in loss of generality forresults
2018	IOT - Top Down Survey	Kouicem et al	Blockchain and Software Defined Networking	Gives a detailed description of Internet of Thin	Privacy and security issues			
2019	Smart parking in IoT-enabled cities: A survey	Al-Turjman et al	Recommends a conceptual hybrid-parking model	The various enabling technologies and sensors are overviewed, and the importance of data reliability, security, privacy and other critical design factors is emphasized in this work.	Data reliability, security, privacy and other critical design factors			

3. Implementation Methodologies

The proposed solution in this work is carried out as follows:

Step 1: Acquisition of Data:
The city of Montreal has monitoring cameras installed on all major streets of the city. The images from these cameras are constantly uploading onto their website after short time intervals. In our framework this data is used. The image data obtained from these monitoring cameras is used to train the Convoluted Neural Network to identify pedestrians, peak

pedestrian density hours (through the timestamps provided on these images), and pedestrian patterns. To successfully pull the data constantly from this website a python program was developed which saved the images and categorized them based on the Street name, timestamp, and date. A few of the images obtained are shown below:

The acquired images were used to train the CNN to not only detect pedestrians, but also to detect any distorted images that could then be discarded. The TensorFlow high-level Kera's API was used to create the classification model for these images. The first step was to identify and discard distorted images, after which they could be used to train the CNN for pedestrian identification.

Step 2: Training Data

Around 3000 images were pulled from the website and used to train the CNN. The images comprised of different angles, and different roads during different times of the day. The data was divided into training and testing data. 90% of the images were used for training the CNN, and the remaining 10% were used as test to check the classification capabilities of the trained CNN. The CNN was trained solely to identify pedestrians. The output image would consist of a box placed around the pedestrians identified. The number of pedestrians identified, street name, and the timestamp are then saved in a separate spreadsheet. This data is then used to draw patterns, pedestrian densities, and any other required data.

Step 3: Alerts Issuance

The analyzed data present in the spreadsheet is constantly sent onto the Cloud where it is analyzed for any discrepancies.

As soon as a discrepancy is detected, or an issue is encountered, the corresponding message is sent to the devices of pedestrians in that vicinity, or other emergency devices by triggering the respective IFTTT custom applets. This data is then also used to control the traffic signals. The ESP8266 NodeMCU development Boards connected to the traffic lights can be used to achieve this purpose. The micro-controller will receive messages from the Cloud database via the Cloud MQTT protocol and thus act accordingly. This could involve controlling the traffic signals by increasing or decreasing the timers, flashing the lights on the pedestrian paths when a pedestrian cross, by sensing motion through the PIR motion sensor, or any other required control. The Cloud server could also be used to issue alerts and warning to nearby emergency services during dire circumstances.

AnyLogic for Simulation and Modeling

The tool AnyLogic multimedia simulation modeling tool was used for simulating pedestrian densities, and other patterns on the roads. The software also contains a special density tool to achieve this purpose.

4. Discussion

The training of the CNN using nearly 3000 images proves to have an accuracy of nearly 97%while detecting pedestrians in the test images. This accuracy tends to increase further as the number of images pulled from the website are increased. The proposed solution successfully issues alerts, notifies pedestrians in the vicinity of the area under observation, and controls the traffic system accordingly as needed. The system trades-off latency in the alerts issuance with the cost-effectiveness of the proposed solution. This slight latency can be easily avoided if more reliable and more expensive sensors are incorporated into the system.
In this section we provide a comparison of our proposed system with an existing similar solution for enhancing pedestrian safety. This section also provides the advantages of our system and its limitations which could lead to potential discrepancies or inaccuracies in the system.

The work titled *“Midgar: Detection of people through computer vision in the Internet of Things scenarios to improve the security in Smart Cities, Smart Towns, and Smart Homes”* by *Garcia et al (2017)* explores the principal hypothesis of using Computer Vision in the Internet of Things to utilize pictures as sensors and identify people successfully. The work succeeds in proposing an architecture that integrates Computer Vision in an IoT platform, and thus provides a way to enhance pedestrian security by successfully identifying and analyzing people in the images. The table below compares and contrasts the features of the solution proposed in this work and the technique proposed in our work.

Table 1. Comparison between system proposed in this work and the paper titled *“Midgar: Detection of people through computer vision in the Internet of Things scenarios to improve the security in Smart Cities, Smart Towns, and Smart Homes”* by *Garcia et al*

	Midgar	**Our system**
Core Technology used	Computer Vision module (developed in python) is used in combination with image processing techniques to search for objects in the image which can be matched to people, things etc. The aim being to insert the use of Computer Vision in the Internet of Things. This involves training the computer to identify objects using a set of images.	In this work too, a convoluted neural network is trained using a set of nearly 3000 images to identify pedestrians in the image. The main aim is to identify pedestrians in CCTV footages using a CNN to aid pedestrian security.
Issuance of alerts	This work only aims to identify the objects in images using Computer Vision.	This solution not only identifies pedestrians in images in real-time, but also issues alerts to nearby pedestrians during emergency situations. The analyzed data is also stored on the cloud from where alerts and messages can be sent to nearby emergency authorities. This data is also used to control the pedestrian and traffic lights as needed during dire situations.
Accuracy & Reliability	An accuracy of 100% for True positives and True negatives for upper-body detection, and 100% for True negatives and 34.38% for True positives in head and shoulders detection is achieved using this technique. The system is thus quite reliable	This solution shows an accuracy of 97% for detecting pedestrians in images. As the training image size is increased, this percentage increases. Thus ~100% accuracy can be achieved with a larger image set. The system is thus reliable
Cost effectiveness	This solution is budget friendly and cost effective	The system is budget friendly and cost effective

The Figures 1 and 2 below show the sample input image obtained from the City of Montreal website. The CNN is able to identify pedestrians and cyclists and store an output image with the pedestrians and cyclists marked in it. The output images are then used to draw pedestrian patterns, pedestrian density, and any other relevant information that could aid in pedestrian safety.

The timestamps on each image help identify the peak hours during which the pedestrian density is highest. For our model, we took sample images of the Guy Street/St. Catherine street crossing.

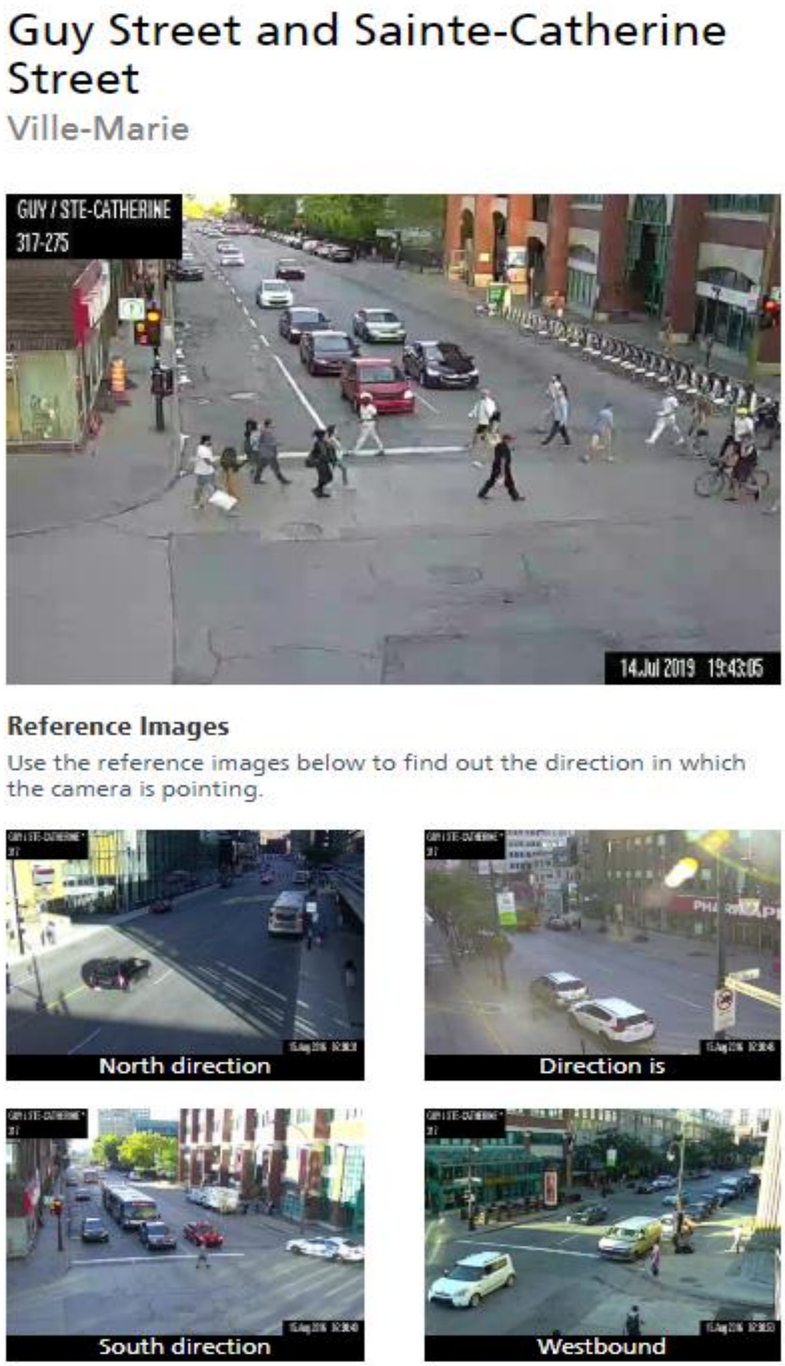


Figure 4. A Sample Raw Input Image obtained from City of Montreal website

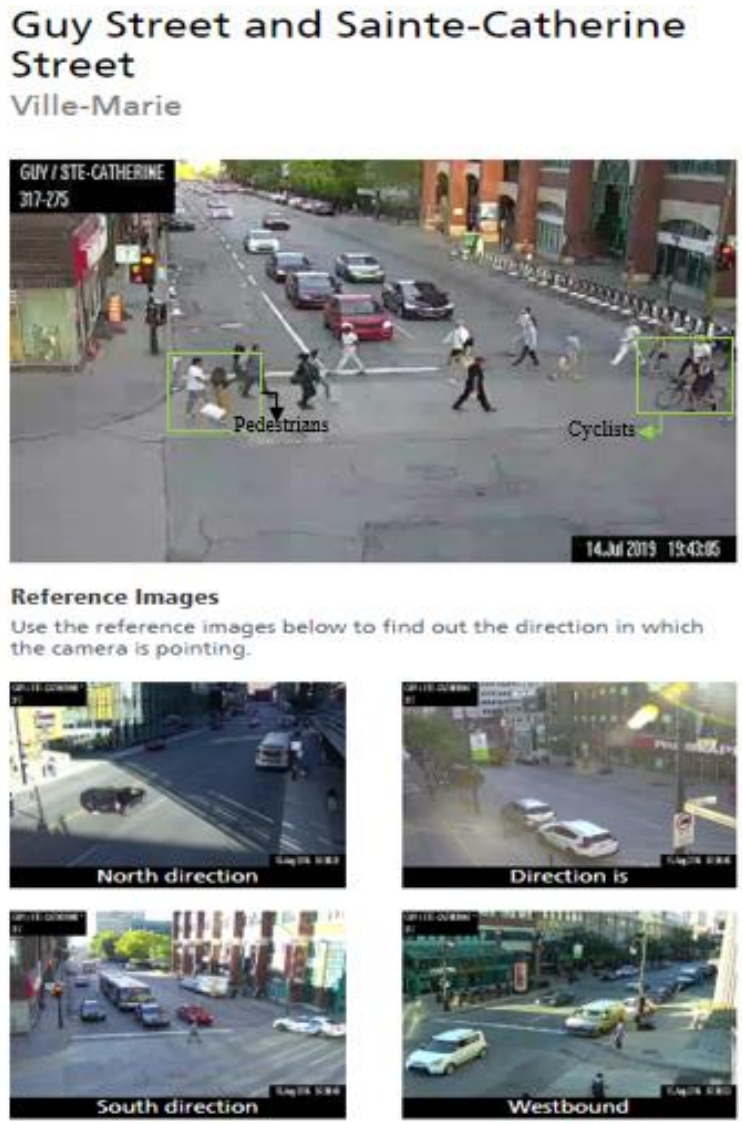


Figure 5. Output Image created by identifying Pedestrians and Cyclists

The system faces certain limitations which need to be addressed. It was observed during data collection that many images were distorted for certain time stamps. The CNN thus also had to be trained to separate the distorted images so as to avoid any discrepancy in identifying pedestrian patterns, densities etc. This required additional effort and time, thus making the system setup more tedious. Another disadvantage is that to have constant access to the image data, it is essential that the city IP cameras keep functioning properly and a stable internet connection is maintained for successful and constant access to the IP camera footage. Any discrepancy in these could lead to the loss of real-time images, and thus loss of pedestrian safety services during those hours. This real-time image data could also be affected by severe weather conditions or other unforeseen circumstances.
The algorithm employed to detect the pedestrians and cyclists in the images is not very complex and is efficient to use. It was observed that it was able to identify the pedestrians and cyclists with an accuracy of nearly 97%. Distorted images were not tested for this detection as they were separated by the CNN before processing for pedestrians and cyclists. Another advantage that the system possesses is the efficiency of the Alert Issuance module. The real-time alerts are issues within few milliseconds of detection of any emergency situation provided the network remains stable and internet access is constant. The traffic and pedestrian lights handlings are done at the edge using micro-controllers employed at the Traffic signals, and thus does not possess any latency as it does not require cloud server access. However, all the data is uploaded onto the cloud for record and analytical purposes.

The system is extremely reliable and efficient. Moreover, it is extremely cost-efficient and easily adoptable by city governments. The system can enhance pedestrian security and emergency services response during dire situations.

Further development and enhancement of the system would require special measures for handling unstable IP camera access and severe weather conditions. More algorithms can be developed that could potentially train the CNN to detect pedestrians even in distorted images, or an additional tool could be utilized to enhance the clarity of the distorted images. Moreover, a central application could be developed for easier issuance of alerts in a more cost-effective manner.

Another work "*Development of countermeasures to effectively improve pedestrian safety in low-income areas*" by *Pei-Sung Lun* 2019 analyses of low-income pedestrian-vehicle was obtained on the basis of two aspects: demographic factors, road environment, and how these demographic factors influence severity in a pedestrian crash (based on severity data). The crash frequency modelling results show that major influential variables of higher pedestrian crash frequency include four demographic factors like proportions of older adults, commuters using public transit or biking, people with no education level and zero-car ownership, three road environmental factors (densities if discount stores and fast food restaurants. The injury severity modelling results show that a dark not – lighted condition is the most influential variable for severe injury pedestrian crashes, and the number of impaired pedestrians and aggressive drivers also greatly increases the probability of severe injury. Based on the analyses results A wide range of statistical methodologies has been developed to describe the relationship between crash frequency and a set of explanatory variables the negative binomial (Poisson-Gamma) regression model was used to quantify the factors that affect the occurrence of pedestrian crashes, and logistic regression, or logit regression or logit model, was used to quantify the factors that affect the severity of a pedestrian injury. Injury severity was described as a binary variable (1 ¼ severe injury, including fatality or incapacitating injury; 0 ¼ others). The assumptions of equal mean and variance of events in the Poisson distribution sometimes make it unsuitable for real-life situations, as there is a possibility of under-dispersion and overdispersion. In such cases, the negative binomial distribution was proposed as a generalization of the Poisson distribution since it has the same mean structure as Poisson regression and has an extra parameter to model the over-dispersion. The Poisson regression model can be written as

(a) Pedestrian crash frequency: negative binomial (Poisson-Gamma) model

$$P(y_i) = \frac{\exp(-\lambda_i)\lambda_i^{y^i}}{y_i!} \tag{1}$$

P(yi) is the probability of curve segment i having yi crashes per given period and λi is the Poisson parameter for curve segment i, which is equal to curve segment ith expected number of crashes per given period, E(yi). The Poisson regression model can be estimated by specifying the Poisson parameter as a function of explanatory variables by typically using a log-linear function.

where Xi is a vector of explanatory variables and b is the vector of regression coefficients. To address this over-dispersion issue, the NB model can be derived as

$$\lambda_i = \exp(\beta X_i + \epsilon_i) \tag{2}$$

where Xi is a vector of explanatory variables and b is the vector of regression coefficients. To address this over-dispersion issue where exp(ei) is a gamma-distributed error term with mean 1 and variance a. The negative binomial probability density function can be described as

$$P(y_i) = \left[\frac{1/\alpha}{(1/\alpha)+\lambda_i}\right]^{1/\alpha} \frac{\Gamma\left[(1/\alpha)+y_i\right]}{\Gamma(1/\alpha)y_i!} \left[\frac{\lambda_i}{(1/\alpha)+\lambda_i}\right]^{n_i}$$

(3) Logistic model measures the relationship between categorical dependent variables and one or more independent variables by estimating probabilities using a logit function as the link function, which is a cumulative logistic distribution. The logistic model, also named the binary logit model, is expressed as

$$P(y_i = 1|X_i) = \Phi(X_i\beta) = \frac{\exp(X_i\beta)}{1+\exp(X_i\beta)} \quad (4)$$

where P denotes the probability of the injury severity (yi) of crash observation i; b is the vector of regression coefficients; Xi is the vector of explanatory variables for crash observation i;
and F is the cumulative distribution function of the logistic distribution. The maximum likelihood estimation (MLE) technique was used to estimate the coefficients of the logistic
model. The geographic analysis and statistical modeling of the identified variables (inputs) produce results (outputs) such as significance of percentage or level of car ownership, significance of percentage of older population, marginal effects of demographic factors, marginal effects of roadway characteristics, geographic trends, and so on.
The geographic analysis and statistical modeling of the identified variables (inputs) produce results (outputs) such as significance of percentage or level of car ownership, significance
of percentage of older population, marginal effects of demographic factors, marginal effects of roadway characteristics, geographic trends, and so on.
This study developed a demographic-based methodology to analyze critical factors associated with pedestrian crash frequency and injury severity in low-income areas, presented the analysis results and major findings, and developed recommendations that resonate with a given area's demographics. For demographic and social factors, major influential variables
include proportions of older adults, commuters using public transit or biking, people with a low education level, and zerocar ownership. For road environmental factors, major influential variables include number of traffic signals per census block group, number of bus stops per mile, and proportion of higher-speed roads in a census block group. For neighborhood land use attributes, major influential variables include densities of discount stores, convenience stores, and fast-food restaurants. Additionally, darkenot lighted condition is the most influential variable for severe injury pedestrian crashes. The number of impaired pedestrians and aggressive drivers
also greatly increases the probability of severe injury. Based on the demographics-based analysis and results, this paper makes specific recommendations for both engineering countermeasures and pedestrian safety education/ outreach plans that resonate with a given area's demographics to effectively improve pedestrian safety in low-income areas.
On the other hand, the proposed work provides an intelligent and economical solution which can provide efficient pedestrian safety system in rural as well as urban areas with lower investments. The system analyses real time data which can be used to process the number of travelling pedestrians, bike riders and pets if any. The pre-processed data can be used for various purposes and can be helpful for future research purposes.

The advantages of the system outweigh its limitations, and thus this system can be incorporated into the current traffic management systems to enhance pedestrian security and emergency services by a large margin. The pedestrian pattern and density data could also be used by the government for other purposes beneficial to the city.

5. Conclusion

This work presents an efficient solution that can aid in enhancing pedestrian safety in a cost effective, and reliable way. The issue of pedestrian safety is of utmost importance as the traditional systems for pedestrian safety pose many limitations and disadvantages that render them relatively ineffective. The technique proposed in this paper aims to eliminate those limitations and provide a reliable and extremely efficient system. This camera data collected for each street by Montreal's government is used to train a neural network using simulation and Tensorflow, which then identifies pedestrian patterns that are observed during each time of the day. The neural network is trained to identify the number of pedestrians in the streets, peak hours at which pedestrian density is maximum, streets which have most pedestrian density throughout the day, and various other patterns. This data can then control the Pedestrian and traffic lights, issue warnings onto the pedestrians' smartphones in the vicinity of the risk area etc. This proposed solution has been compared and contrasted with several other solutions that currently exist. Its efficiency, reliability, and cost-effectiveness make it a better alternative than most other works. Moreover, this technique can also provide information and alerts to emergency services and other higher authorities. This not only makes it ideal for pedestrian safety, but also aids in developing Smart Cities.

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