TrafficPulse: Interactive Real-Time Traffic Jam Analysis & Forecast System

Team 43

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1 Introduction

[Q1>]We're creating a tool that lets people see and understand how busy the roads are in different parts of Singapore based on real-time Singapore Traffic Images. The system would also be predicting the traffic throughput for the chosen location and time range selected by the user.[<Q1]

[Q2>]Despite prior visualization efforts, integrating interactive data analysis and enhancing accessibility in network traffic data remains a challenge. Today, most systems that show traffic conditions depend on videos or data from people's GPS devices. These methods can be complex and costly. We believe that just using pictures from traffic cameras, which are simpler and cheaper to manage, can be just as effective. Moreover, while there are tools that show traffic, they do not have interactivity at the core of their systems. [<Q2]

2 Literature Survey

Christoph Hardegen et al. [1] utilizes deep neural networks to predict and categorize network traffic throughput into three classes, extending beyond conventional binary classification. While its approach can be applied to our project to predict vehicular traffic from images, the paper prioritizes network data over image data.

Rafed Muhammad Yasir et al. [2] presents a model using a Support Vector Regressor to predict traffic congestion based on factors like day, time, and weather, closely relating to our project. However, its effectiveness and accuracy in varied real-world scenarios may need additional validation.

There has been traffic analysis by employing fixed-position drones instead of traditional camera-based surveillance for traffic analysis and performing vehicle recognition and tracking using Mask RCNN. The study has established that complex traffic situations can result in inaccurate calculations. Due to the limitation of the acquired video data, this initial study only considers some basic traffic metrics. [3]

Mahmoud Abbasi et al. [4] thoroughly reviews deep learning applications in Network Traffic Monitoring and Analysis (NTMA), offering valuable insights into using DNNs, CNNs, and RNNs for traffic prediction and classification beneficial to our project. However, the applicability of these models for segmenting and analyzing individual traffic lanes or directions may be limited.

A. H. Akoum et al.[5] use Canny Edge Detection and vehicle background separation via spatial location. Their approach, however, did not provide any visualizations or aggregations across time as a part of their analytics, even though they provide their research as software. We use the Singapore traffic camera data to both provide the much-needed aggregated traffic information and also to analyse data in real time.

Other papers included used their own datasets where the recordings were proprietary videos rather than images [6]. These recordings were also recorded from a rooftop, and their camera angles and resolution might be quite different since they used IP-based cameras. Their ideas can, however, be used in a future iteration of our work, especially by government agencies, where we have access to live video data from cameras.

We also believe [7] would be useful for us as their work involves a transformation of the problem into a 2D detection task centred on identifying rotated bounding boxes within the bird's eye view (BEV). This would help us identify the poses of the car, hence helping us determine what road a given car is travelling on. This can be used to calculate aggregate information about the car track as well.

B. Qi et al[8] implemented a deep learning model using the Single Shot MultiBox Detector for detecting road objects, with detection accuracy measured by mAP. While precise in traffic analysis, its adaptability in diverse urban scenarios and performance during rapid changes or nighttime remain concerns.

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3 Proposed Methodology

Interactive Dashboard Overview:

Dong Hyun et al.[9] introduced a web-based visual system using uncertainty quantification and DWT for network traffic data analysis, with heatmap visualization for clarity. Adapting this, we plot crucial data points on a Singapore map. [Q3>]Uniquely, our method combines road camera photos, geographic positions, timestamps, and weather data to predict traffic. Users can click on map points to view current and forecasted traffic, as well as historical patterns, enhancing understanding with live, user-friendly data. Our system will expose a color-coded map (as per the traffic congestion) to the user who can zoom into an area to get traffic throughput data along with real-time feed. We also allow the users to specify the time duration for retrieving the traffic conditions.[<Q3] We curate our dataset via the LTA Datamall traffic API. It includes the following features: location (longitude, and latitude), timestamp, a CCTV image snapshot of the road and cars indicating

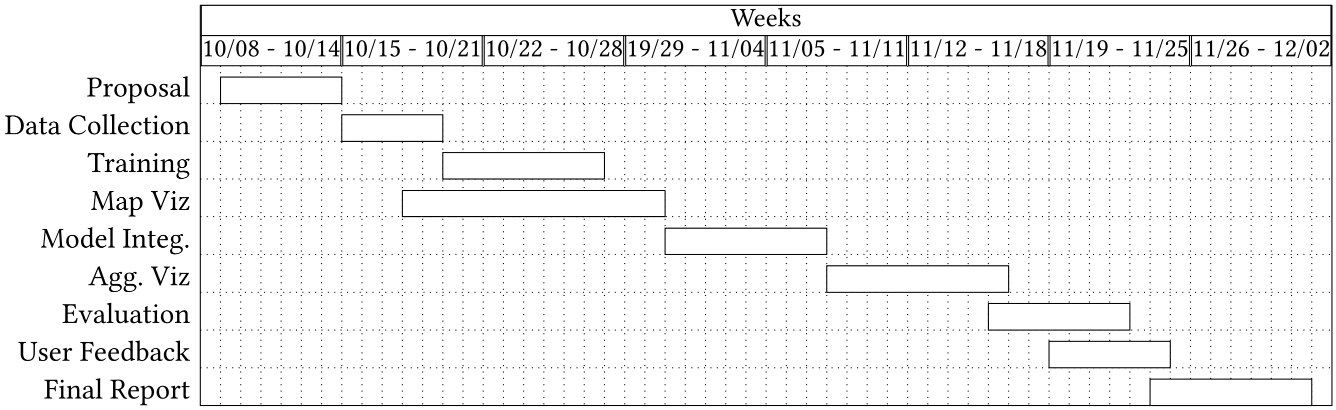

Figure 1: [Q8>]**Gantt Chart. Each member will make equal contributions for each task.**[<Q8]

traffic at that time and location. We create a time-series data, ranging from 2016-present.

Traffic Congestion Forecasting Baseline: As our data is temporal, we find the work of Hrvoje Novak et al. [10] on travel time forecasting essential. We build on their traffic forecasting methods to build our baseline models using Simple Moving Average, and ARIMA models. For our evaluation metric we go ahead with RMSE.

Multi-Modal Traffic Congestion Forecasting: Our main innovation lies in our novel multi-modal approach. Moritz Neun et al.'s work [11] conduct traffic state forecasting using spatio-temporal methods, we take inspiration and taken it a step further. Our models incorporate images, weather data, timestamps, and location information. To model across these diverse input domains, we leverage models like ConvLSTM and Vision Transformers.

Forecasting Time Resolution: Users have the ability to interactively select a location on the map and decide the future time resolution for predictions. The options available are hourly predictions upto 24 hours or daily predictions up to a week. This timeframe is chosen deliberately to tap into observable weekly and 24-hour traffic patterns.

Lane Separated Traffic estimation: A key challenge we face is intelligently separating traffic congestion estimation for each lane in the CCTV camera snapshot. Leveraging Xingang Pan et al.'s Spatial CNN (SCNN) for road lane detection [12], we employ SCNN to efficiently capture lane continuity and detect lanes. This integration enables granular traffic congestion estimation for each lane.

[Q7>]We will be using free GPU services: Google Colab & Kaggle Kernels to have a zero cost approach.[<Q7]

3.1 Evaluation

Midterm Checks:[Q9>] A map with colour coded locations indicating congestion, each location opens a window with traffic analysis dummy UI. Have curated the historic data via API from 2016-present, and integrated real-time API to our Dashboard's backend. Have the baseline ARIMA models working and report preliminary RSME results on dataset.

Finals Checks: Traffic Analysis window shows the latest snapshot, with forecasting knobs like hourly or daily time resolution. Upon forecasting the model returns the traffic congestion trend graph from present to selected end time. ConvLSTM, VisionTransformer decoder models that take images are implemented and compared with baselines. The system works smoothly, with minimal lag or processing delays, even when handling larger data sets end to end.[<Q9]

4 Conclusion and Discussion

[Q4>]City officials can utilize our tool to optimize road management and planning, such as adjusting traffic light timings and planning roadwork, while businesses can strategically place ads in high-traffic areas.[<Q4]

[Q5>]Success entails providing a visual, interactive representation of Singapore's traffic conditions, aiding city planners and benefiting businesses financially. Success measurement involves comparing daily traffic congestion frequencies before and after tool deployment.[<Q5]

[Q6>]Our work involve risks like live traffic image fetching limitations and prediction inaccuracies, the tool promises a potentially revolutionary, cost-effective system for transforming city traffic management and business advertising.[<Q6]

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