Snap to Help: An Automated System for Accident Severity

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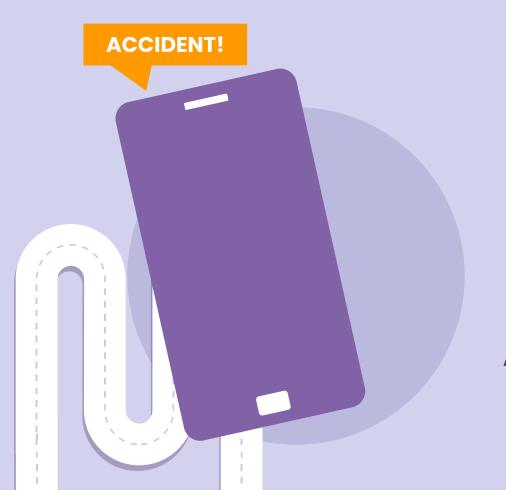
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01

About Accidents



Accidents can happen anytime

In the last five years,

Every day

Someone gets injured in a road traffic accident in Singapore

9 deaths

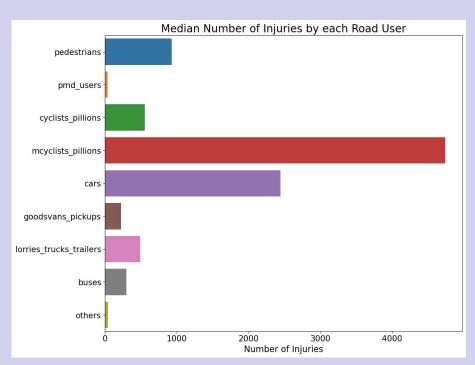
Per month as a result of road traffic accidents in Singapore



Source: SingStat



Findings on Injuries

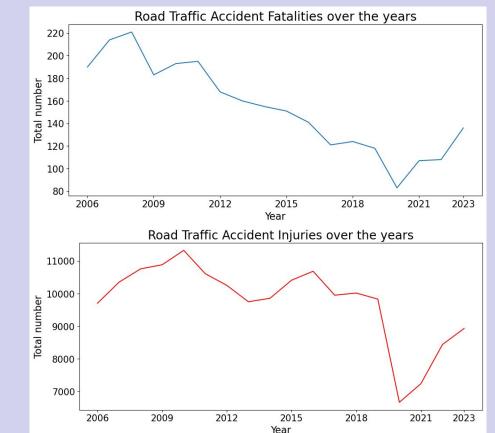


- Motorcyclists & pillions are the most vulnerable to getting injured in an accident
- Car driver & passenger injuries are very high, more than 2000
- Pedestrians, bicycles are also prone to injuries due to impact and fall

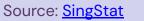


Source: SingStat

Casualty numbers over the years



- Number of fatalities had been decreasing from 2010
- Number of injuries fluctuates at around 10,000 every year
- **Sharp drop** in both numbers in 2020
- After 2020, the numbers are going up every year





What to do right after an accident

- Check if anyone is injured. Call for an ambulance if anyone is in need of immediate medical attention.
- 2) Report the accident to the police. (if needed)
- Gather evidence of the accident scene. Take photos.
- 4) Have your vehicle towed. (if needed)



Wheel Lift Towing



Flatbed Towing



Source: <u>EMAS Recovery</u>

Profiles



Hannah

Hannah is in charge of **deploying rescue teams in SCDF**. She receives a call when emergency help is required after an accident. There were some cases where **callers exaggerate or underestimate** the situation. When the first responder team arrives and assesses the situation at the scene, **sometimes additional resources are needed**.

Aaron is an **officer from LTA**. When there is a traffic accident, he receives a call on the LTA hotline. If the accident cannot be seen via a traffic camera, he is **unable to ascertain how severe** the accident is. Afterwhich, he deploys a recovery crew with **tow trucks** and **road marshals** to the scene, with a chance of **over deploying or under deploying**.



Agron



Possible Solution



They hope to have a **centralised system** where the affected driver or witnesses can **upload images** of the accident. The system should enable **quick identification** of accidents and **prompt responses** from various services.



Aaron

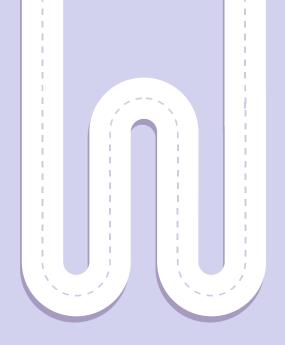




02

Problem Statement



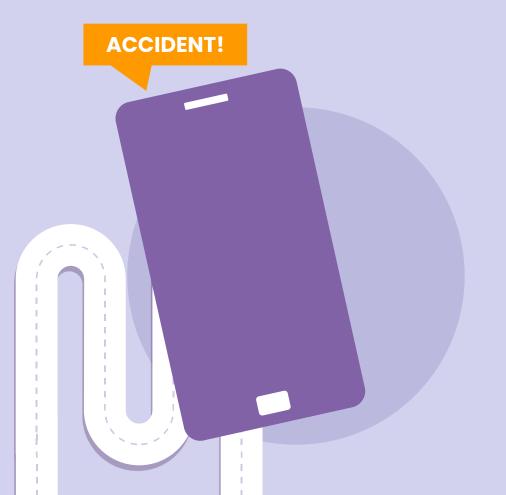


Problem Statement

How can we develop an automated system capable of analysing images from traffic cameras or phone cameras to classify accidents into five severity classes accurately?







03

Dataset & Modelling



Image Dataset

Folder Directory

Fire 120 images Minor 100 images Moderate 120 images No Accident 400 images Severe 170 images











Image dataset was split into train, validation and test sets.



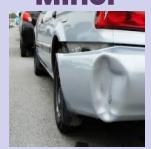


Severity Classes

Fire



Minor



Moderate



No Accident



Severe





Classification Model	Train Accuracy	Valid Accuracy	Train Loss	Valid Loss
Self-trained CNN	0.9923	0.6626	0.0696	1.6319
MobileNetV2	0.9392	0.8098	0.2255	0.5140
VGG19	0.7710	0.6687	0.5937	0.8421
EfficientNetB4	0.2881	0.4601	3.9087	5.2880

Accuracy = Correct Predictions

Total Predictions



Classification Model	Train Accuracy	Valid Accuracy	Train Loss	Valid Loss
Self-trained CNN	0.9923	0.6626	0.0696	1.6319
MobileNetV2	0.9392	0.8098	0.2255	0.5140
VGG19	0.7710	0.6687	0.5937	0.8421
EfficientNetB4	0.2881	0.4601	3.9087	5.2880

Train and Validation Accuracy is **too low** for EfficientNetB4.



Classification Model	Train Accuracy	Valid Accuracy	Train Loss	Valid Loss
Self-trained CNN	0.9923	0.6626	0.0696	1.6319
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For CNN, it is **overfitting** to a **large extent**. It also has the **highest validation loss**.



Classification Model	Train Accuracy	Valid Accuracy	Train Loss	Valid Loss
MobileNetV2	0.9392	0.8098	0.2255	0.5140
VGG19	0.7710	0.6687	0.5937	0.8421





Classification Model	Train Accuracy	Valid Accuracy	Difference
MobileNetV2	0.9392	0.8098	0.1294
VGG19	0.7710	0.6687	0.1023



Classification Model	Train Accuracy	Valid Accuracy	Difference
MobileNetV2	0.9392	0.8098	0.1294
VGG19	0.7710	0.6687	0.1023

Although VGG19 **overfits less** (just by a small margin), we want our chosen model to be of **high accuracy**. Thus, we pick **MobileNetV2** for further **fine tuning**.





Fine Tune MobileNetV2

Classification Model	Train Accuracy	Valid Accuracy	Difference
MobileNetV2	0.9392	0.8098	0.1294
MobileNetV2 with Regularization	0.8339	0.8221	0.0118





Fine Tune MobileNetV2

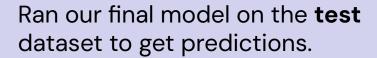
Classification Model	Train Accuracy	Valid Accuracy	Difference
MobileNetV2	0.9392	0.8098	0.1294
MobileNetV2 with Regularization	0.8339	0.8221	0.0118

After fine tuning, there is **less overfitting** as our model is able to **predict better** on unseen data.



Test Dataset

Fire Minor Moderate No Accident Severe 20 images 20 images 20 images 20 images 20 images **B**6





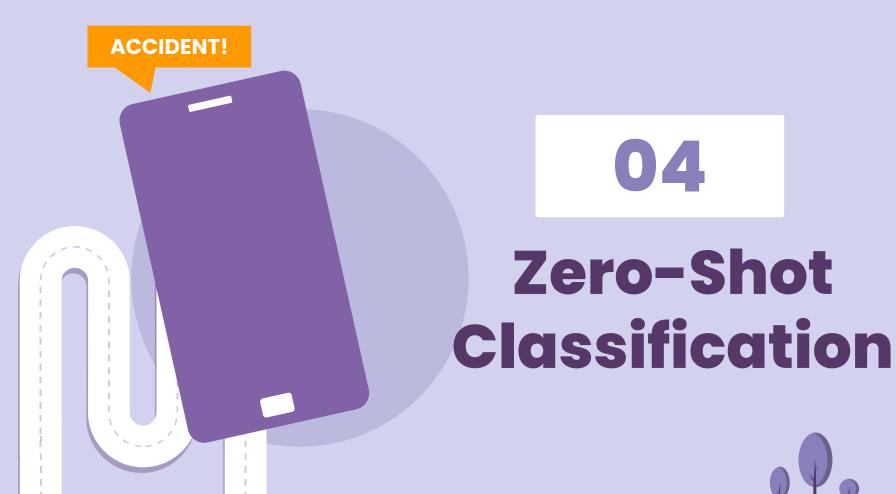






- Does well on fire, no_acc and severe classes
- Many wrong predictions for minor and moderate classes



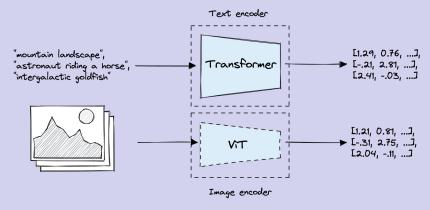




Zero-Shot Image Classification

Zero-shot image classification uses a model that was **not explicitly trained** on data containing **labeled examples** from those specific categories. It is typically a model that has been trained on a **large dataset of images** and **associated descriptions**.

Contrastive Language-Image Pretraining (CLIP) by OpenAl





Source: <u>Hugging Face</u>, <u>Pinecone</u>

Candidate Labels

```
candidate_labels =
["fire accident", "minor accident",
"moderate accident", "no accident",
"severe accident"]
```





Candidate Labels

candidate_labels =
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"severe accident"]



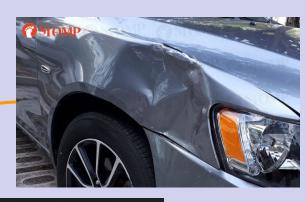






Candidate Labels

```
candidate_labels =
["fire accident", "minor accident",
"moderate accident", "no accident",
"severe accident"]
```



```
[{'score': 0.6180193424224854, 'label': 'minor accident'},

{'score': 0.16647666692733765, 'label': 'no accident'},

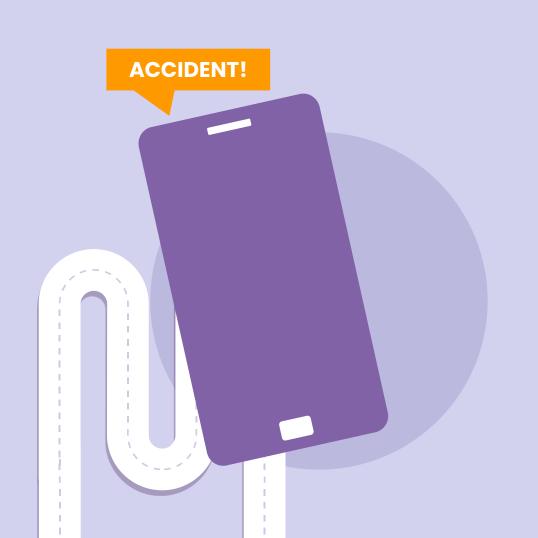
{'score': 0.15892527997493744, 'label': 'moderate accident'},

{'score': 0.05580728128552437, 'label': 'severe accident'},

{'score': 0.0007714481325820088, 'label': 'fire accident'}]
```

Source: Stomp





05

Streamlit Demo



Hannah & Aaron



Hannah

Now, Hannah has a **clearer idea** on the severity of the accident. Thus, she can decide the **type of resources / emergency vehicles** to deploy to the scene, whether there is a fire or someone stuck in the car. If there is an **overturned vehicle**, it is **very likely** that someone is **severely injured** and require immediate assistance.

Aaron is now able to make a **definite decision** on which **kind of tow truck** to deploy to the scene. He can also clearly decide on **how many road marshals** are required depending on the severity of the accident.



Aaron





06 Learnings



Limitations

Inaccuracy in some classes

Difficult to predict minor and moderate accidents. Some images look similar, thus unable to be predicted correctly by our model.

Unclear Definitions

While 'fire' and 'no_acc' are classes with clear identities, there are no clear definitions for a minor, moderate or severe accident. It was also not mentioned by the author of the dataset.

Data Formats

Deeper analysis cannot be done on severity of an accident without other details such as number of people injured and estimated speed before collision.





Data Augmentation

More transformations (saturating / cropping) can further help to generalize and expand our accident dataset. There may be clearer distinctions between minor and moderate accidents.

Relate severity of accident to injuries suffered

An injury can be classified into different tiers based on Injury Severity Score (ISS). Relating this to accident severity can be done as future research.

Using dashcam for severity analysis

Severity of an accident can also depend on the speed of the vehicles involved. Using a dashcam can potentially estimate the speed of the vehicle.





07 Conclusion

Conclusion

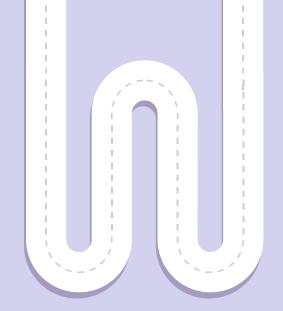
We conducted **exploratory data analysis** on road traffic accidents in Singapore and **classified images** of accidents into **five severity classes**.

Other agencies or authorities may **benefit** from our severity classifier. Vehicle insurance companies can use this to **calculate insurance claims**, while the Traffic Police can use this for **further enhancements of road safety**.



THANK YOU

Do you have any questions?



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