



Deep Learning Based Facial Mask Detection

CS5242 Final Project

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Date: 14 Nov 2022

Content

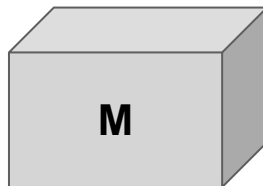
- **Problem Statement**
- **Data Preparation**
 - data collection
 - data pre-processing
 - data analysis
- **Model Architecture**
 - baseline models: MLP, CNN, LSTM
 - proposed model: vision transformer
- **Discussion and Analysis**
 - result visualization
 - project novelty
 - future research directions

Problem Statement

- **Objective:** accurate facial mask detection under covid-19
- **Methodology:** DL-based multi-class image classification

$$Acc = \mathbb{E}_{\langle i, c \rangle \in D} \mathbb{1}_{\text{argmax}(p(i))=c}$$

i



mask?

no mask?

no face?

Data Preparation

- data collection
- data pre-processing
 - cleansing
 - augmentation
- data analysis

Data Preparation - Collection



- Google/Baidu
- Sleep time/IP address
- With mask/Without mask/Irrelevant

Data Preparation - Pre-processing

- Data pre-processing **increase sample size/variety** and **reduce data noise**

data cleansing

- remove deprecated images
- re-assign wrongly-classified images

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**face centered -
image cropping**

- crop images to focus on the face part with **face_recognition** library

Data Preparation - Pre-processing

- Data pre-processing **increase sample size/variety** and **reduce data noise**

data cleansing

- remove deprecated images
- re-assign wrongly-classified images

face centered - image
cropping

- crop images to focus on the face part with `face_recognition` library

data augmentation

- resizing
- random cropping
- affine transformation
- rotation (45/90/180/270)
- flipping
- lightening
- Gaussian blurring
- salt and pepper noise

Data Preparation - Analysis

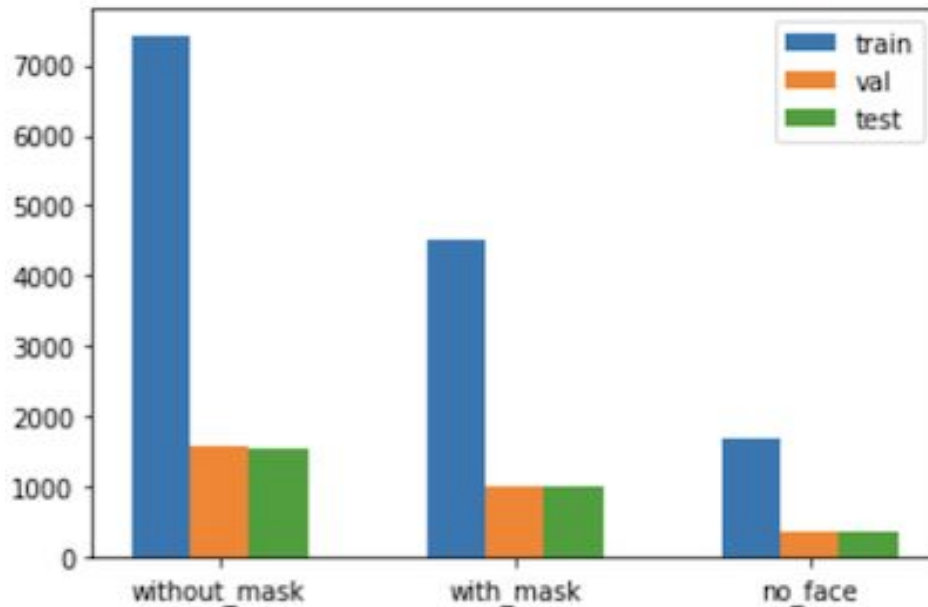
- Data splitting

- Train set : val set: test
set: **8 : 1 : 1**

```
train:
without masks: 7427
with masks: 4527
no faces: 1672
val:
without masks: 1563
with masks: 986
no faces: 370
test:
without masks: 1554
with masks: 1015
no faces: 350
```

Data Preparation - Analysis

- Data splitting
- Data visualization
 - bar plot to show the number of images from three categories.

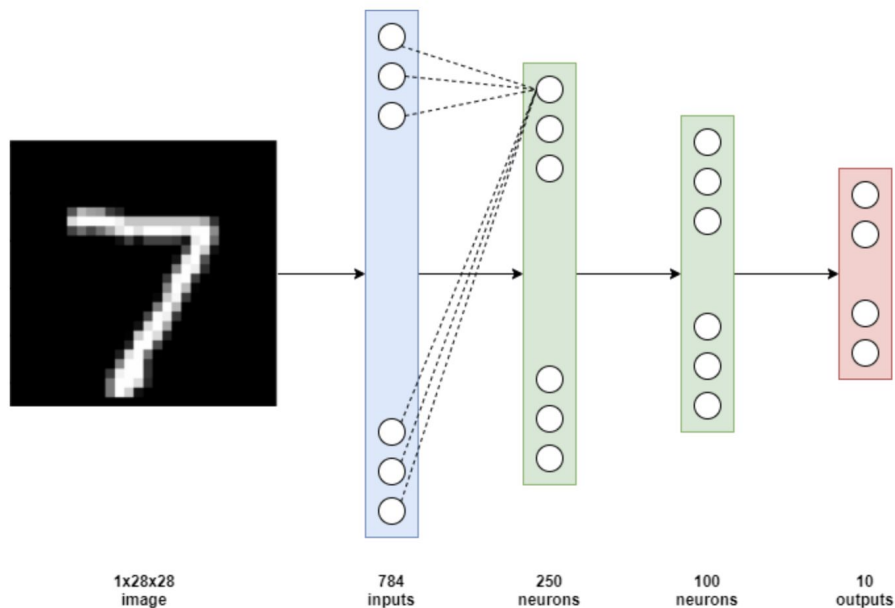


Model Architecture

- MLP
- CNN
- LSTM
- Vision Transformer

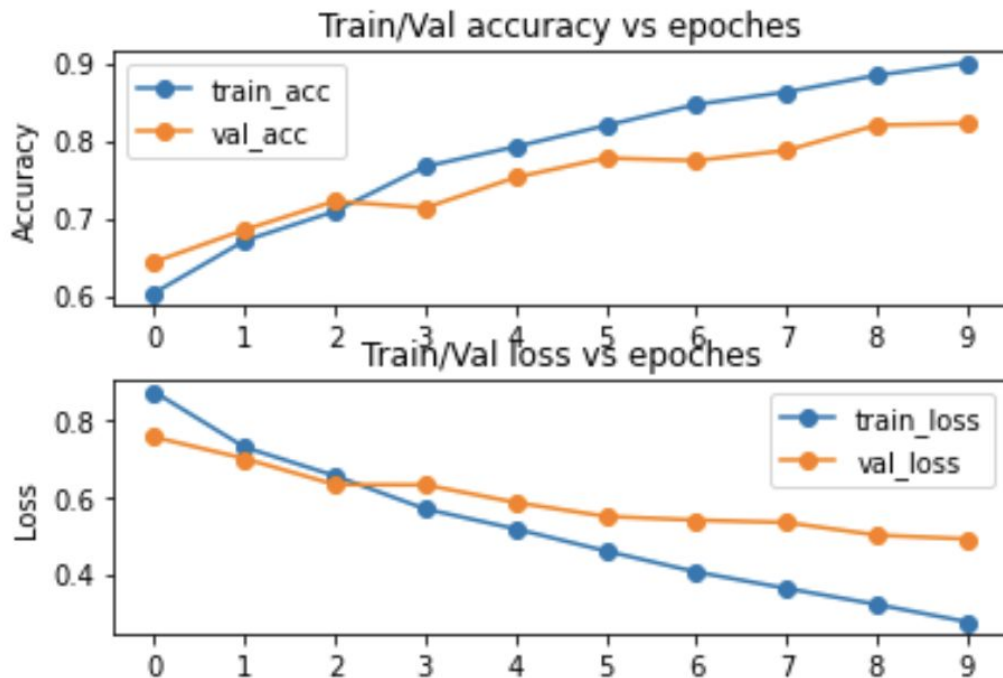
MLP

- model architecture: fully connected layers



MLP

- model architecture
- performance: 79%

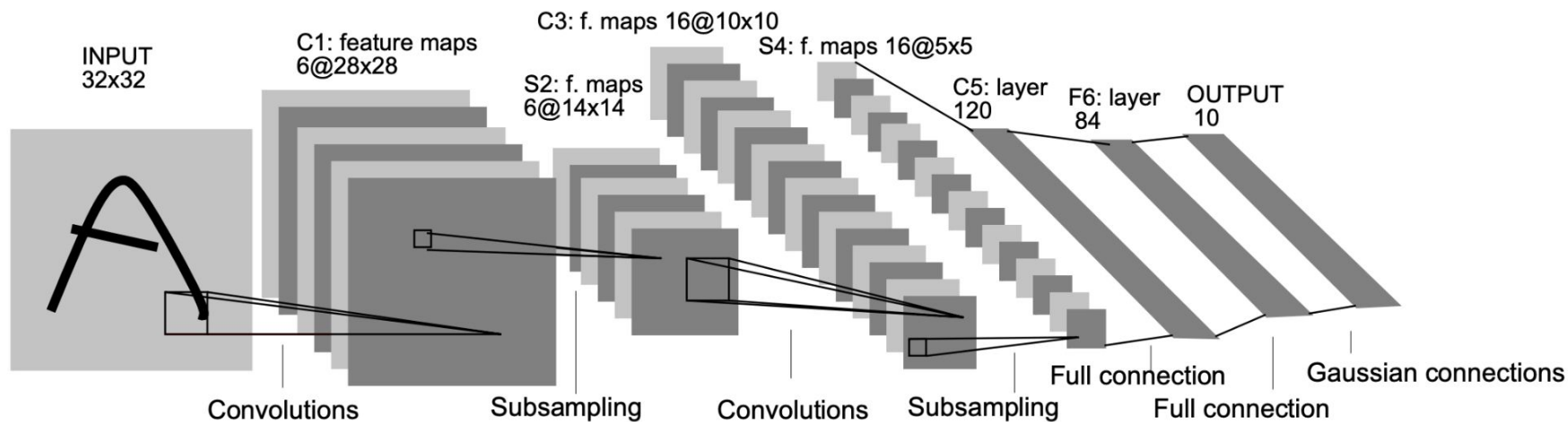


MLP

- **model architecture**
- **performance: 79%**
- **pros** and **cons**:
 - easy to generalize
 - quick predictions
 - large #parameters

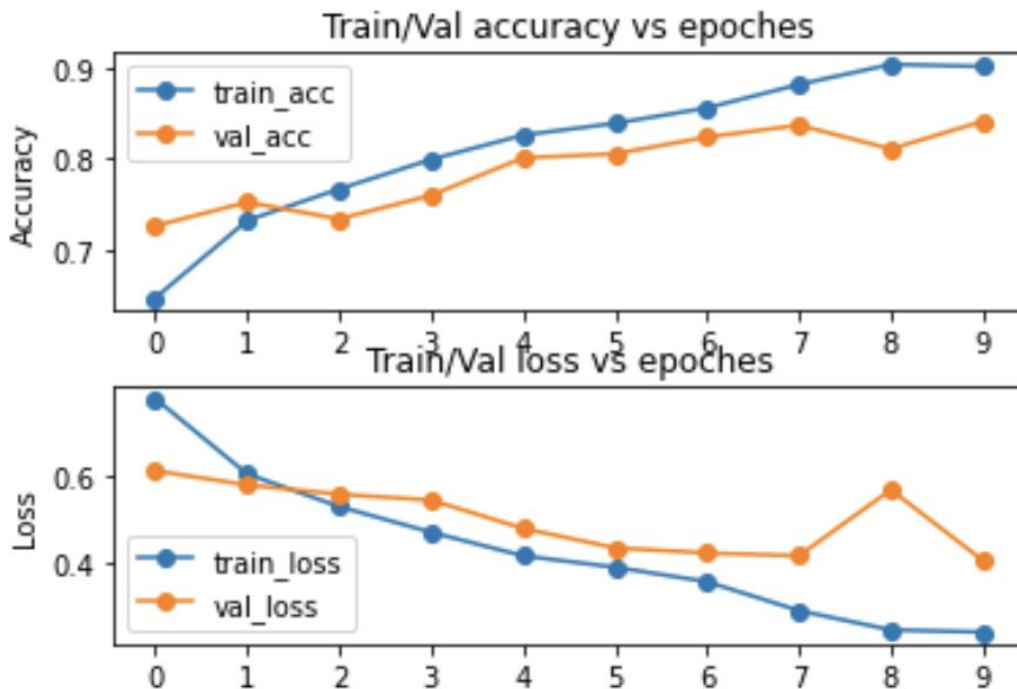
CNN

- model architecture: grey-scale -> conv layers -> linear layers (referring to LeNet 5)



CNN

- model architecture
- performance: 83 %



CNN

- **model architecture**
- **performance: 83 %**
- **pros and cons**
 - image feature capturing
 - parameter sharing
 - parallel computation
 - over-emphasize individual features vs whole object

LSTM

- model architecture:

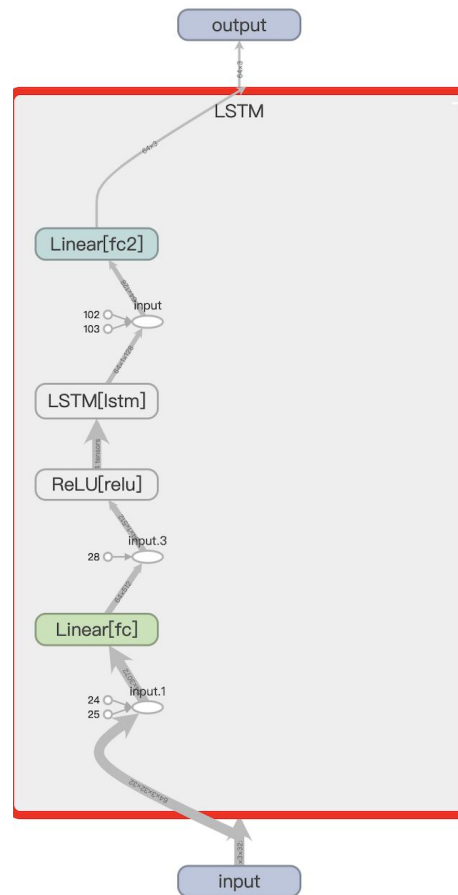
batch size = 64.

linear layers(flatten,
(64, 3*32*32)->(64, 512)) ->

relu(activation) ->

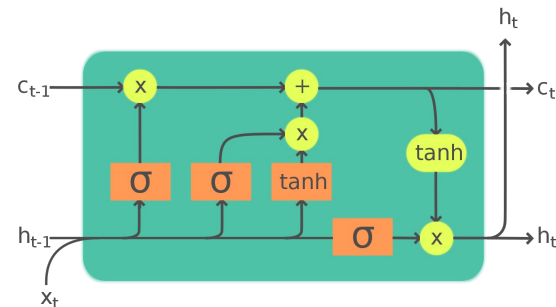
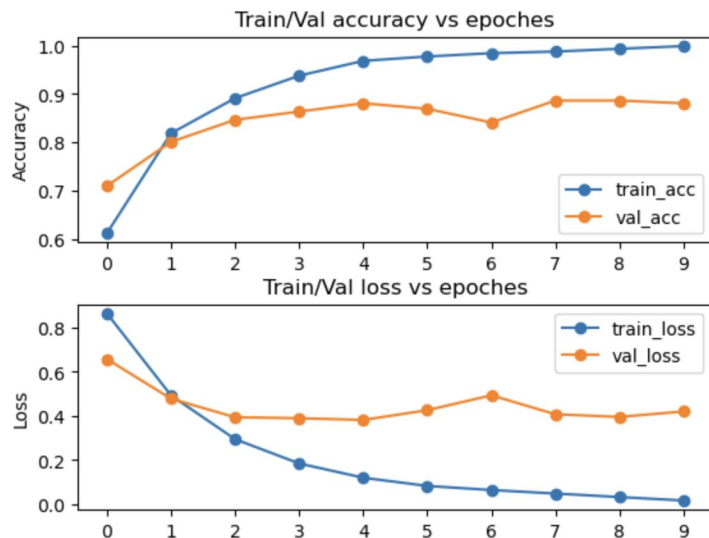
lstm(unsqueeze,
(64,1,512)->(64, 1,128)) ->

linear layers(flatten,
(64, 128)->(64, 3)).







LSTM

- performance: 81%



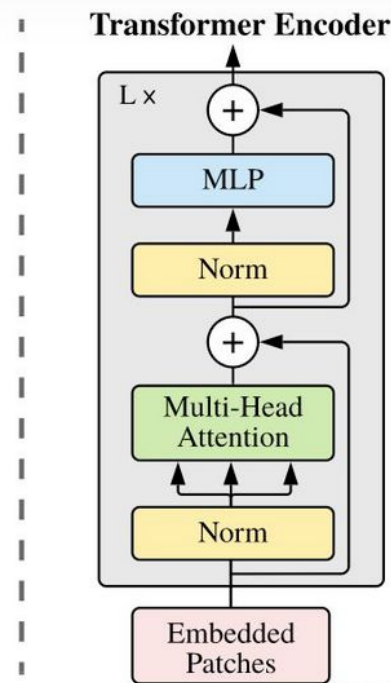
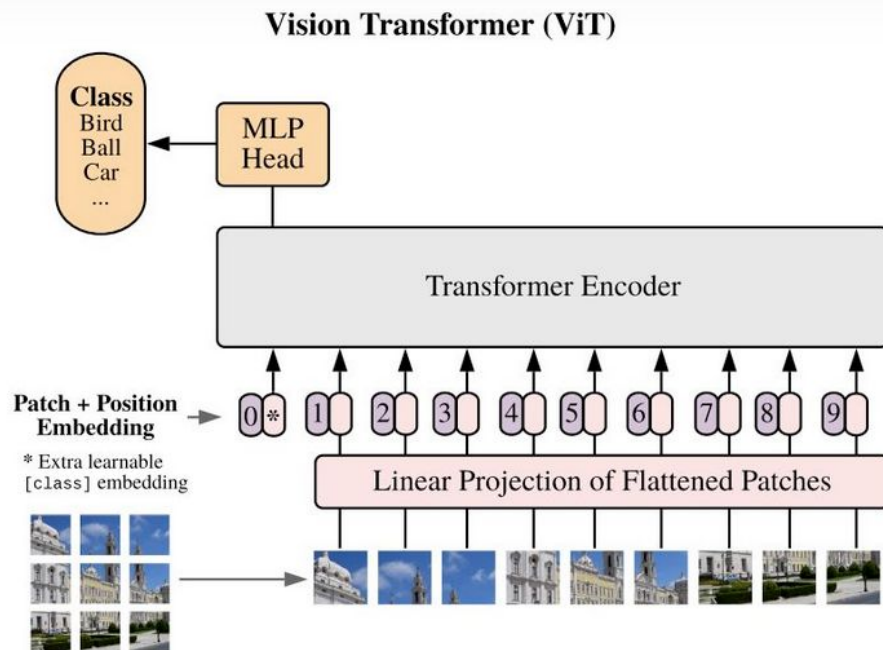
Legend:

Layer	Componentwise	Copy	Concatenate
			

LSTM

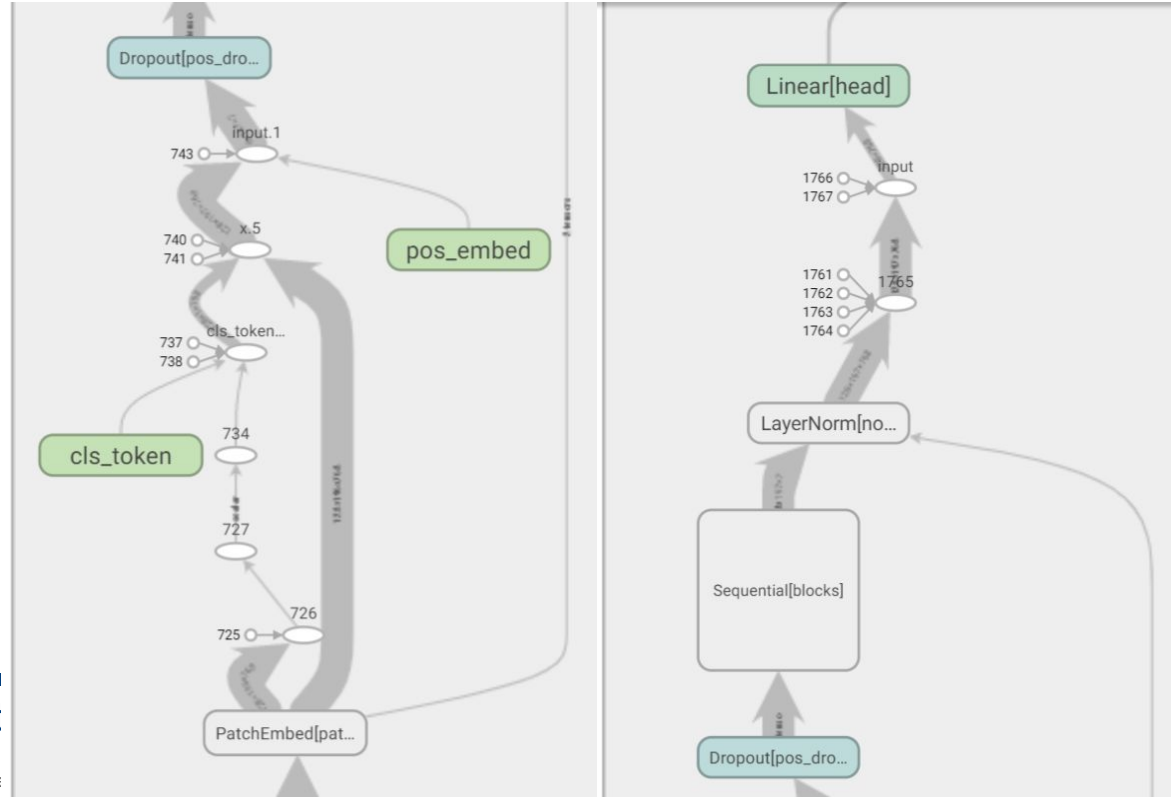
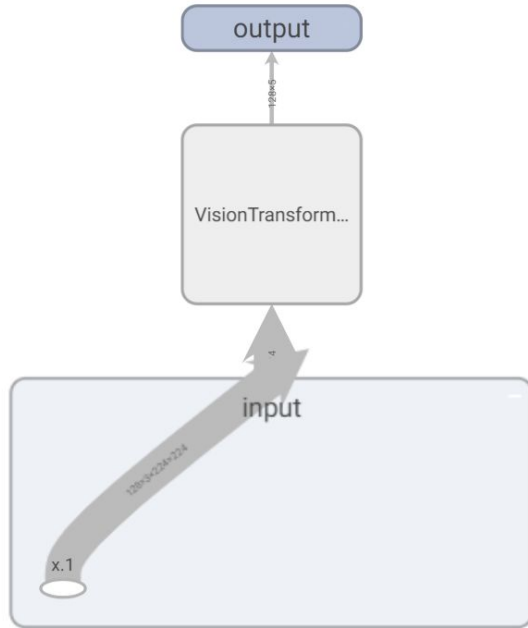
- **model architecture**
- **performance: 81 %**
- **pros**
 - less prone to vanishing gradient problem in RNN
 - avoid the long-term dependency issue
 - parameter sharing
- **cons**
 - easy to overfit
 - hard to implement Dropout
 - takes longer training time

Vision Transformer



DN @辣大辣条

Vision Transformer

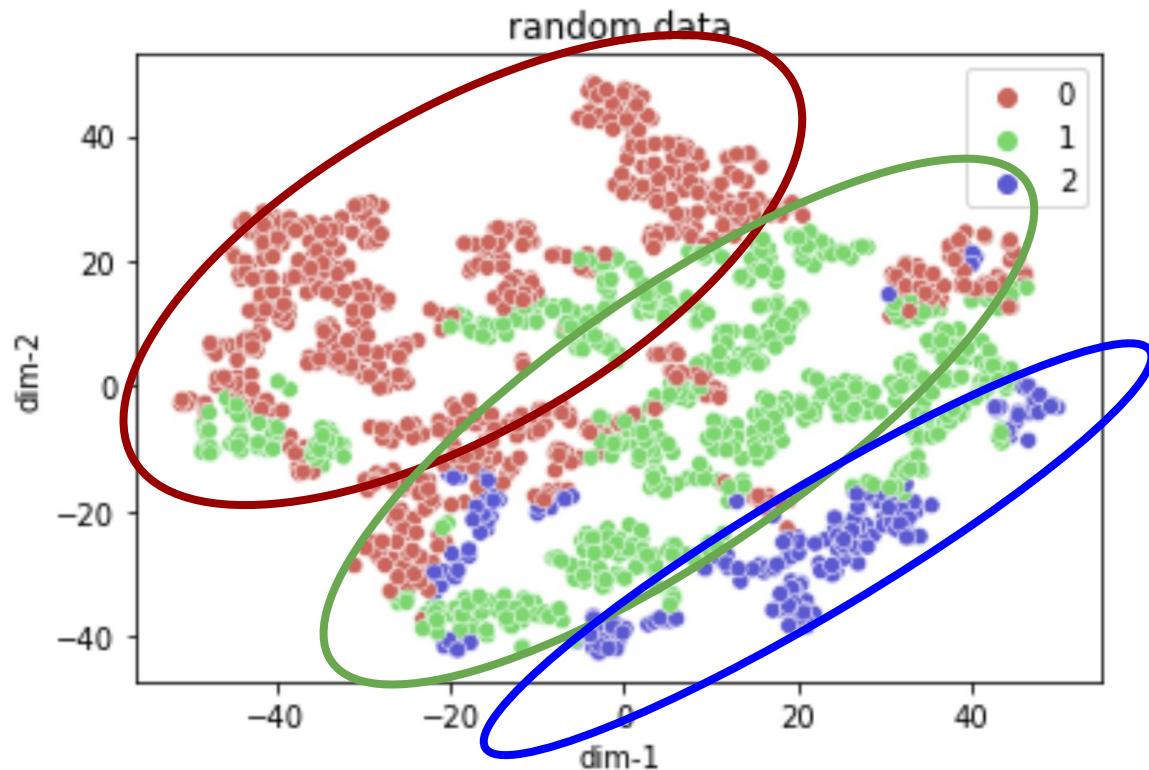


Discussion & Analysis

- results visualization
- project novelty
- future research directions

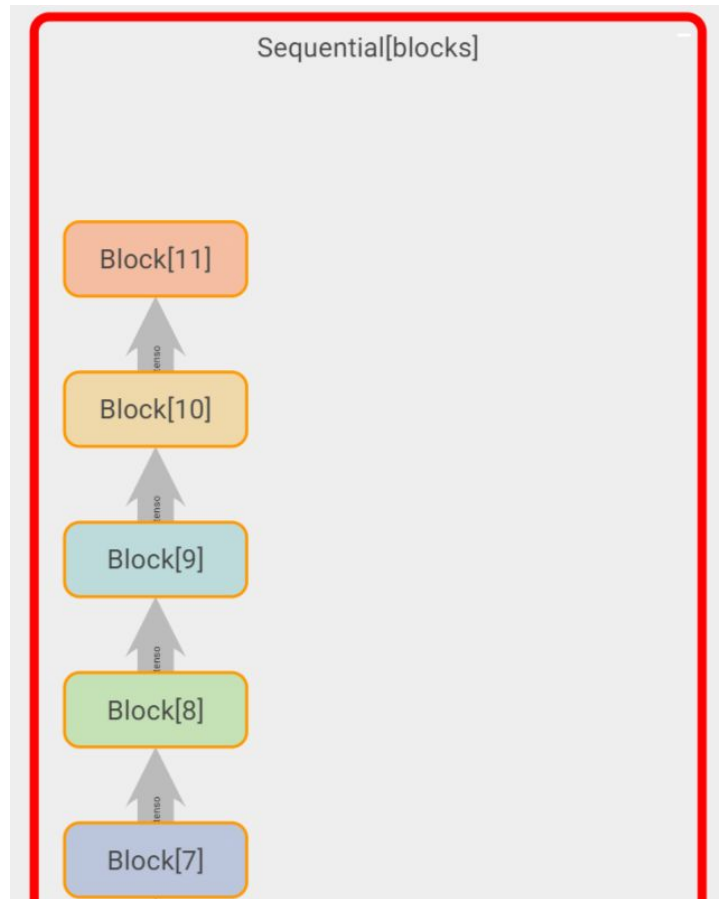
Result Visualization

- tSNE visualization of 1600 samples on 2D space



Project Novelty

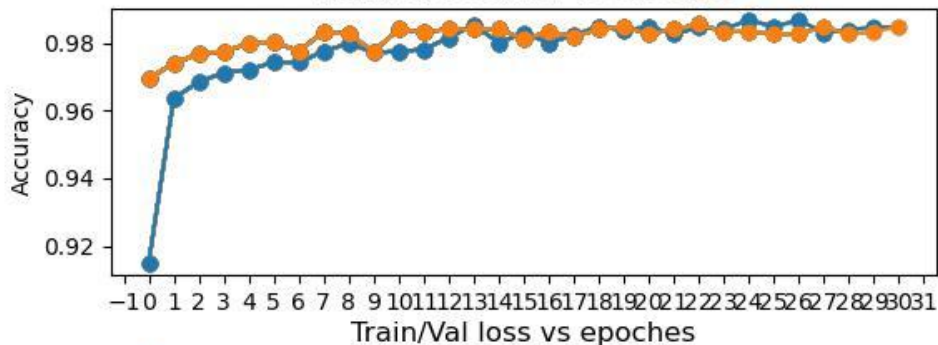
- **Proposed a suitable model architecture**



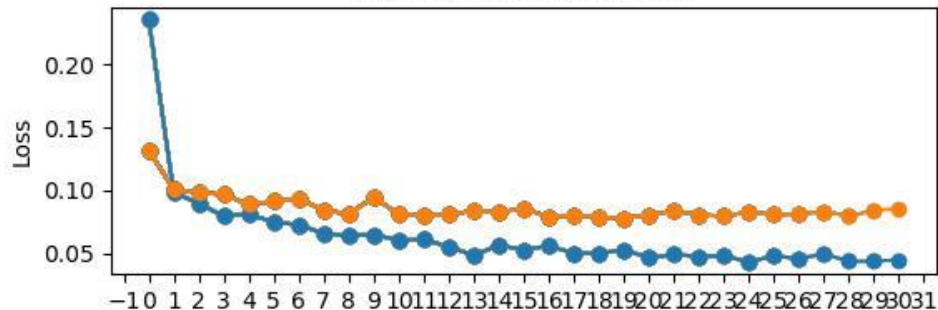
Project Novelty

- Created a new dataset from scratch

Train/Val accuracy vs epochs



Train/Val loss vs epochs



1.jpg



3.jpg



4.jpg



9.jpg



10.jpg



11.jpg



19.jpg



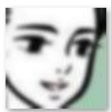
20.jpg



21.jpg

Project Novelty

- Implemented 14 data augmentation methods



0_blur.jpg



0_brighter.jpg



0_change.jpg



0_crop.jpg



0_darker.jpg



0_GaussianNoise.jpg



0_horizontal.jpg



0_move.jpg



0_rotate90.jpg



0_rotate180.jpg



0_rotate270.jpg



0_salt.jpg



0_scale.jpg

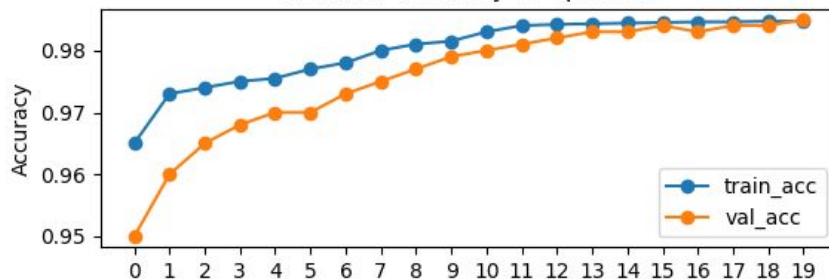


0_vertical.jpg

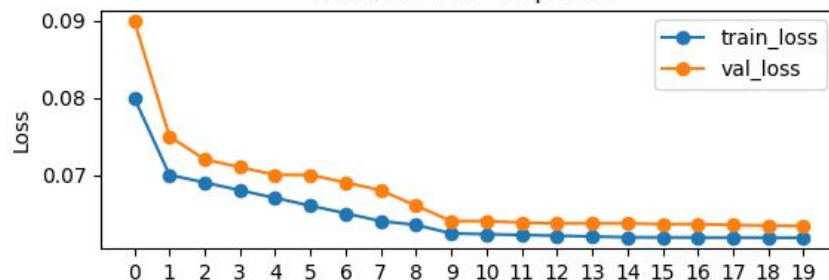


1_blur.jpg

Train/Val accuracy vs epochs



Train/Val loss vs epochs

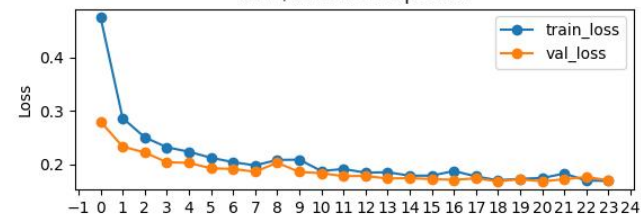
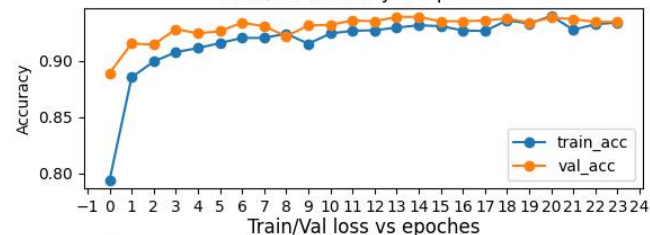


Project Novelty

- Used Smart training strategies

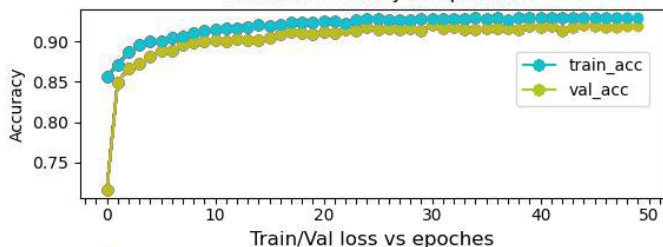
Learning Rate 0.0005

Train/Val accuracy vs epochs

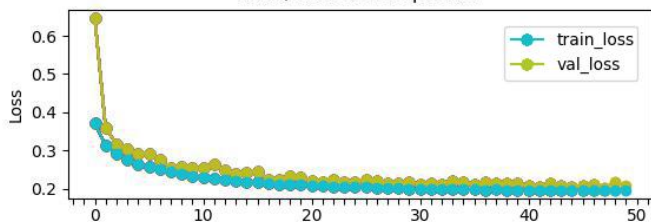


Learning Rate 0.0001

Train/Val accuracy vs epochs

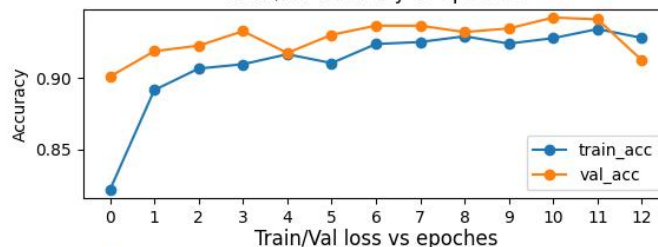


Train/Val loss vs epochs

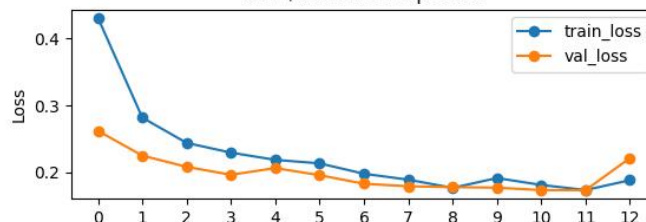


Learning Rate 0.001

Train/Val accuracy vs epochs



Train/Val loss vs epochs



Project Novelty

- Proposed a suitable model architecture
- Created a new dataset from scratch
- Implemented 14 data augmentation methods
- Used Smart training strategies
- **Proposed a model with highly generalizable**

Limitations

- Size of dataset
- Training with more GPU
- Ensembling and optimization

Future Research Directions

- Model pruning
- Ensemble learning: hard voting and soft voting
- Adversarial training

Acknowledgment

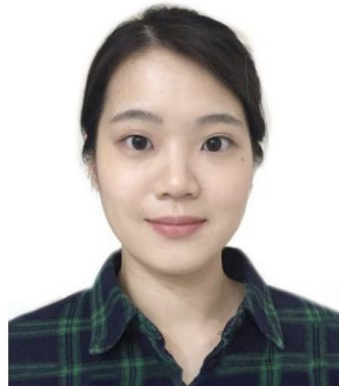
- We'd like to thank all CS5242 teaching staffs for their support and guidance through out the learning journey.



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Reference

We have attached our reference sources to corresponding notebooks.