Reducing Bias in Unmanned Aerial Vehicle Facial Recognition

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***Abstract*—Unmanned Aerial Vehicles (UAVs) are being increasingly used, especially for serious applications including surveillance and identification for drone strikes. UAV technology is currently amid a shift from remote human control to utilising Artificial Intelligence (AI) to become fully autonomous. This transitional period has brought to light concerns of biases present in the training data of these systems and the subsequent ethical concerns that arise. Specifically, unbalanced data results in minorities being inaccurately identified by these systems. To address this issue, we must confront the underlying issue of training data imbalance to create a diverse and inclusive dataset which will be reflected in the model. We do this by augmenting the FairFace dataset to include an equal distribution of individuals form various races. We then train a CNN classifier on this dataset to evaluate the improvement. Additionally, we aim to implement algorithmic race based bias analysis techniques to reduce bias without dataset alterations. We find a significant 25% improvement when applying these techniques and outline future applications of our findings.**

Keywords*— *Unmanned Aerial Vehicles (UAVs), Artificial Intelligence (AI), dataset augmentation, bias analysis

I. Introduction

UAVs have evolved from simple theoretical devices to sophisticated autonomous systems poised to reshape various industries, including defence and surveillance. With a projected doubling of the UAV market by 2026, this exponentially growing technology will play a significant role in government and military operations (Leslie, 2020). As UAV technology transitions from human-controlled to fully autonomous operation, the integration of artificial intelligence (AI) brings forth new challenges, particularly concerning training biases (Kärkkäinen, 2019) (MDPI, 2023). In this context, the root causes of bias are due to an overrepresentation or underrepresentation of certain demographic groups in training data. Almost all modern and popular data sets have the dominant race as White. The below figure outlines the racial distribution among popular datasets in the field.

Consequently, when identifying individuals the model will be more accurate for races which the data favours, introducing ethical concerns. It has been statistically demonstrated that bias in training datasets resulted in darker skinned and female individuals ranging between 18-30 years old being inaccurately identified up to 34% higher than lighter-skinned female faces in a similar age range (Kärkkäinen, 2019). Hence, solving this issue is vital to ensure equality and fairness in our societies. Real-world incidents, such as the deployment of autonomous UAVs in military operations, highlight the urgency of mitigating biases. In addition, the disparity between detection accuracy in faces due to differences in race creates concern when deployed in military and surveillance applications. This begs the question: "How can we reduce and quantify the impact of biased training data to improve accuracy for UAV facial recognition".

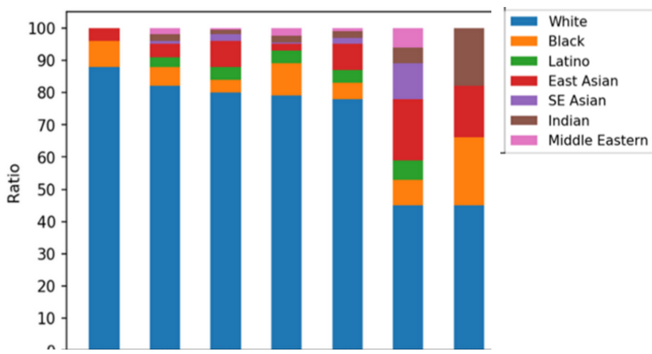


Figure 1. Distribution of Races in Various Datasets (Hsu & Chen, 2015)

We continue this paper with a literature review in section 2. to elaborate on the current state of the field and the research gaps we aim to address. We formulate our problem in section 3, then in section 4 we outline our data augmentation methodology on a ResNet34 CNN model. In section 5 we outline our results. Subsequently we discuss our findings in section 6 and conclude in section 7. This research and development of solutions will be able to provide insight and awareness to global powers and societies who will have to face the consequences of this technology if it continues to be used without further development into its bias.

II. Related Works

A. Demographic Imbalances in Facial Recognition Systems

Buolamwini and Gebru (2018) outline in their landmark paper that facial recognitions systems which are trained on datasets with demographic imbalances will achieve higher error rates for underrepresented groups. This frames our research problem to enable us to target a solution. They find that particularly women and people of colour are underrepresented, which perpetuates existing biases leading to unfair outcomes for citizens. They find that these biases occur because AI models trained on these datasets learn patterns that reflect the skewed nature of the training data. This finding guides our solution to focus on dataset improvements.

B. Controlled Training Data

Wiegand, Pimental, Rutterfors, Vollmer & Roberts (2023) explains why it is important to collate training data that is controlled. Stating that just "collect(ting) a ton of raw data" is not going to improve the model. Datasets are controlled when a model trained separately for each discrete task has less bias than a model that is trained for multiple tasks. This disparity occurs due to the neural network specialising its training for a specific task. This article crucially reveals that if a model is trained for multiple tasks simultaneously its effectiveness is reduced. Hence, it is apparent that a possible solution avenue to explore for bias reduction is race specific identification models. We aim to augment the existing dataset, however this finding provides a valuable research avenue to explore when datasets cannot be altered.

C. Adjusting Model Parameters to Mitigate Bias

Contrastingly, Schroff, Kalenichenko & Philbin (2015) provides valuable insight into utilising machine learning to mitigate biases that can occur in the real world. The paper delves in strategies and solutions that help mitigate race and gender bias utilising model parameters. In their algorithm they found that "emergency room patients who were black were 40% less likely to receive pain medication than white patients" and "women were 2.5 times less likely to be referred to a cardiologist for chest pain" (Schroff, Kalenichenko & Philbin, 2015). This reveals that the data which the algorithm was trained on is inherently biased. Three options are proposed to address this, specifically, pre-processing, in-processing or post-processing of model training. The paper reveals that the creation of a model for each population group could be created to prevent the model becoming skewed towards a majority class which will improve accuracy. However, this approach is more costly and time consuming to achieve. Alternatively, in-processing using adversarial training requires two models, one of which is used to classify and predict the task, and the adversarial model which is trained to exploit a bias. This is applicable when the training data cannot be modified or is inherently biased. The paper fails to address research gaps regarding when the dataset can be modified or how the model can be changed during post-processing.

D. Considerations for Robust Training

Bindemann, M., Fysh, M. C., Sage, S. S. K., Douglas, K., & Tummon, H. M. (2017), reveals that we must consider different angles, lighting conditions, distortion from height, velocity, viewing angles and environmental conditions when training the model. These situations must be addressed to accommodate the wide variety of conditions which UAVs are applied in. Overall, these papers play a crucial role in guiding and validation our approach which will involve modifying the dataset.

III. Problem Formulation

Here we will formally formulate our problem so that we have measurable success criteria. We define our problem through the research question "How can we reduce and quantify the impact of biased training data to improve accuracy for UAV identification systems". To address this, we will attempt bias mitigation techniques on an identification dataset. Specifically, we will augment the dataset to ensure an equal number of samples between classes. Hence our aims are to reduce bias in training data. This will require us to quantify bias in training data. Subsequently, we aim to achieve a low disparity (approximately 5 percent) between class accuracies. Subsequently, we must evaluate the impact of these changes on a per class basis by running a valid comparison study on the two datasets. This will involve training an industry standard model on each dataset and comparing the model performances.

IV. Methodology

To improve accuracy by reducing bias in facial recognition we augment the dataset with images from external datasets to even the samples for each race class. We then quantify the impact of this change via a classification problem. Specifically, we compare the accuracy measures of a ResNet-34 CNN using the TensorFlow 2.13 library model on an unbiased and biased version of the same FairFace (Hsu & Chen, 2015) dataset to classify individuals. Refer to figure 2 to visualise our workflow:

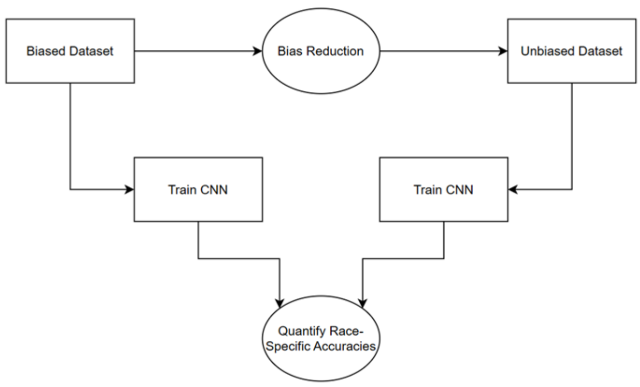
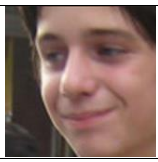


Figure 2. Method Flowchart

The FairFace dataset is split up into a training and test set using an 80/20 split respectively with a random seed of 42. The dataset initially is biased towards white individuals. We reduce this bias by augmenting it with individuals of other races to balance the samples. All images were in a PNG format and augmented images were randomly selected from the datasets outlined in Figure 1 while avoiding duplicate images. There are 7 different categories of races present in the data set: White, Black, Latino, East Asian, Southeast

Asian, Indian, and Middle Eastern. Additionally, the dataset includes labels for age in ranges of 10 and gender. Additionally, we removed all samples with missing values, outliers or errors that can affect our results. The image annotations are contained within a CSV file with a column for the file name and a column for each class. All files were uploaded to Google Drive, which were mounted to a Google Collab workspace to enable collaboration. Below we display some sample images from the dataset to exemplify the range of the dataset:

TABLE I. EXAMPLE DATASET IMAGES

Image		
Class	20-29, Female, White	10-19, Male, White
Image		
Class	30-39, Female, East Asian	40-49, Male, Latino Hispanic

The code is implemented using the following procedure (See Appendix 2 for code):

1. Import libraries including os, NumPy, matplotlib, sklearn, skimage, cv2, seaborn, random, TensorFlow, pandas, torch.
2. Set all random seeds to 42.
3. Mount the google drive to the colab CPU environment.
4. Set file path.
5. Define the ResNet34 architecture (See Appendix 9)
6. Load image files using the 'train' and 'test' CSV files.
7. Encode labels.
8. Train the model using ADAM as the optimiser with a learning rate of 0.001 epochs and 'sparse_categorical-crossentropy' as the loss function. Train the model for biased model for 10 epochs and the unbiased model for 40 epochs using a batch size of 32.
9. Display the epoch/loss chart.
10. Evaluate the model on the test set.
11. Output accuracy and confusion matrix.

V. RESULTS

Here we outline the numerical results of our experimentation. First, we compare the distribution of samples from the original biased dataset to the augmented dataset respectively. This displays a successful reduction in training data bias:

TABLE II. PERCENTAGE DISTRIBUTION OF 'RACE' IN BIASED DATASET

Race	**Count of race**
White	43.93%
Latino Hispanic	10.26%
Black	9.84%
East Asian	9.80%
Indian	9.59%
Southeast Asian	8.93%
Middle Eastern	7.65%

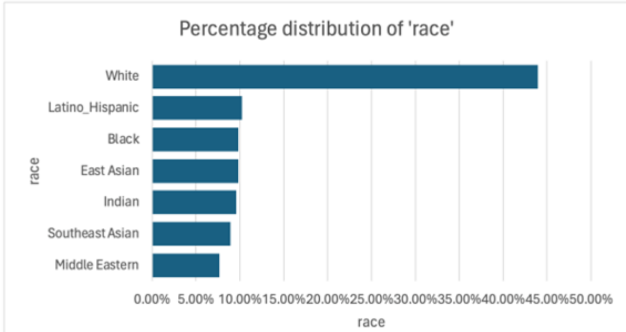


Figure 3. Percentage Distribution of Race in Biased Dataset

TABLE III. PERCENTAGE DISTRIBUTION OF 'RACE' IN UNBIASED DATASET

Race	**Count of race**
White	19.03%
Latino Hispanic	14.82%
Black	14.20%
East Asian	14.15%
Indian	13.84%
Southeast Asian	12.92%
Middle Eastern	11.04%

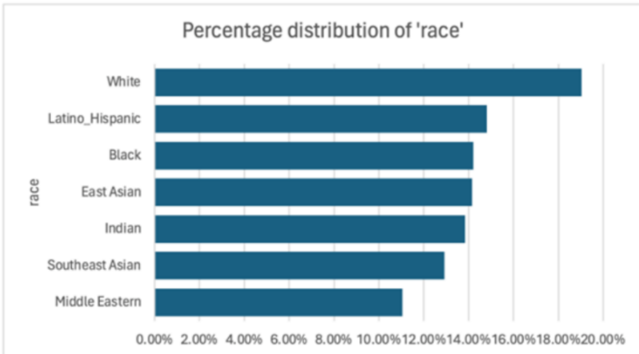


Figure 4. Percentage Distribution of Race in Unbiased Dataset

Here, we quantify the accuracy measures of the models during and after training on each dataset:

TABLE IV. AVERAGE ACCURACIES

Dataset	Accuracy (Test)
Biased	75.01%
Unbiased	93.99%

TABLE V. WHITE

Gender	M	F
Biased	0.98	0.98
Unbiased	0.96	0.947

TABLE VI. BLACK

Gender	M	F
Biased	0.68	0.729
Unbiased	0.951	0.91

TABLE VII. EAST ASIAN

Gender	M	F
Biased	0.748	0.737
Unbiased	0.867	0.932

TABLE VIII. SOUTHEAST ASIAN

Gender	M	F
Biased	0.729	0.72
Unbiased	0.902	0.9

TABLE IX. LATINO

Gender	M	F
Biased	0.674	0.702
Unbiased	0.97	0.953

TABLE X. INDIAN

Gender	M	F
Biased	0.71	0.684
Unbiased	0.959	0.94

TABLE XI. MIDDLE EASTERN

Gender	M	F
Biased	0.744	0.685
Unbiased	0.984	0.867

TABLE XII. SUMMARY STATISTICS

Max	Min	Avg	STDV
0.98	0.674	0.7501	0.1004
0.984	0.873	0.9399	0.0342

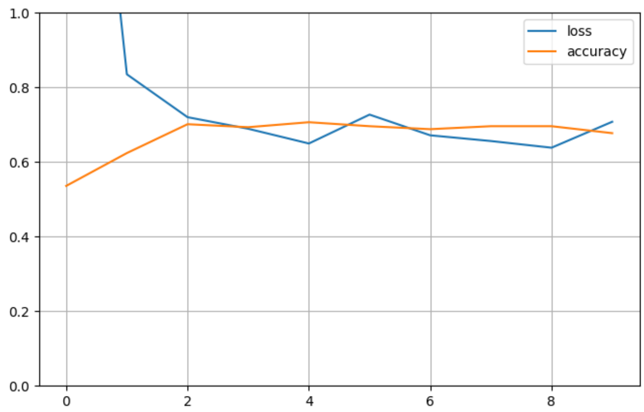


Figure 5. Biased Model History Plot

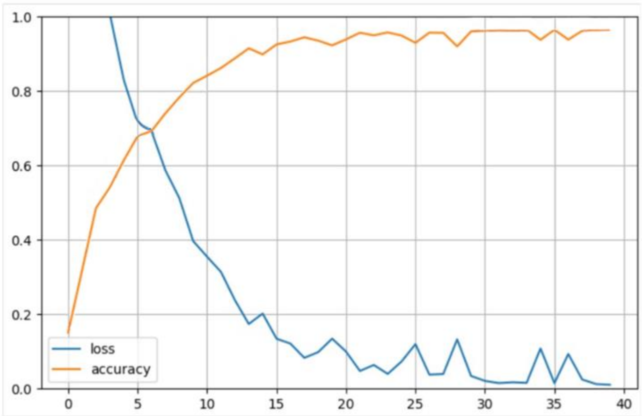


Figure 6. Unbiased Model History Plot

Here we outline our validation and hyperparameter experimentation testing:

TABLE XIII. EXPERIMENTAL RESULTS

Experiment	Person	Test Accuracy
Unbiased (ADAM, LR 0.001, Epochs 40, Batch 32)	William, Dylan, Rob, Justin, Jerry	0.94
Biased (ADAM, LR 0.001, Epochs 10, Batch 32)	William, Dylan, Rob, Justin, Jerry	0.75
Biased (ADAM, LR 0.01, Epochs 10, Batch 320)	William	0.61
Biased (ADAM, LR 0.001, Epochs 10, Batch 32, Removed 2nd Conv Layer)	Dylan	0.68
Biased (ADAM, LR 0.005, Epochs 10, Batch 160, Removed 2nd Conv Layer)	Rob	0.65
Biased (ADAM, LR 0.01, Epochs 10, Batch 320)	Justin	0.62
Biased (ADAM, LR 0.005, Epochs 10, Batch 160)	Jerry	0.70

VI. DISCUSSION

A. Findings

Our research has elucidated several interesting and vital findings to help solve our research question and the outlined major gaps in the fields. We found that augmenting datasets is a successful strategy to reduce bias, as exemplified by our roughly 25% improvement in accuracy. This finding emphasises the importance of quality training data, which is a universally supported trend in the field. Ultimately this illustrates the validity of our results and testifies to the validity our methodology. Further, we replicated our findings amongst team members with equivalent performance indicating the reproducibility of our findings. This was enabled by the necessary hyperparameter settings remaining the same between training and testing of each model. The biased dataset strongly favoured white individuals, while the updated dataset had significantly more equal distribution of individuals. When comparing our results to other state-of-the-art and baseline papers in the field we see that our improved model performs at a breakthrough accuracy (See below table) (Hsu & Chen, 2015).

TABLE XIV. ACCURACY FOR DIFFERENT DATASETS

Dataset	Accuracy
UTK	0.859
LFWA+	0.766
CelebA	0.866

Analysing the race and gender specific data we find further justification for our intuition that imbalanced training data directly correlates to an imbalance in category specific accuracies. Notably, we still see a favouring of white individuals even in the unbiased dataset, possibly due to our inability to completely remove bias due to our dataset constraints. Interestingly, we find the model performs better on men than women, which is explained by the favouring of men in historical contexts which influences dataset creation. However, this disparity is far less than we expected, and is almost negligible, with race accounting for the major discrepancies. Additionally, the standard deviation is three times larger in the CNN trained on the biased dataset as opposed to the unbiased dataset. This indicates that lower quality data introduces uncertainty into AI models in the field of UAV facial recognition. Interestingly, the unbiased CNN took longer to converge on its peek accuracy, requiring 40 epochs. This is explained by the additionally complexity introduced by more and higher quality data. This finding should be applied when training future models.

Additionally, we found changes to hyperparameters could yield significant differences in accuracy and loss. This highlights a future avenue for research as hyperparameter optimisation could mitigate biased datasets. Our experimentation included changes to the learning rates, epochs, batch sizes and model architecture on the unbiased and biased datasets. The "Unbiased" model trained with a learning rate of 0.001, 40 epochs, and a batch size of 32, achieved the highest accuracy of 0.94 on the test set. This suggests that the combination of these hyperparameters and training duration was optimal for the task. Contrastingly, the testing on the biased models found that significant drops in accuracy occurred with higher learning rates (for example 0.01) or modifications to the model architecture (e.g., removal of the 2nd convolution layer). This is exemplified by the results of the biased model with a learning rate of 0.01 and a batch size of 320 achieving a low accuracy of 0.61. This also reveals that the standardised approach of scaling batch size with learning rate was not sufficient to counteract the loss introduced by these modifications.

Moreover, reducing the complexity of the model by removing the second convolution layer resulted in a slightly higher accuracy. This is likely due to a reduction in loss due to less overfitting caused by a simpler model. Overall, these results highlight the importance of hyperparameter selection and dataset augmentation.

B. *Limitations and Improvements*

There are several limitations which should be addressed by future research to increase the reach and significance of our findings. The time and resource constraints did not enable us to explore algorithmic solutions to bias mitigation. This technique when applied in conjunction to dataset augmentation without image addition may yield significant cumulative benefits. Further, this technique could be applied in situations where changing the dataset is not an option, such as in country-wide surveillance programs.

Additionally, we only considered the impact of quantity on datasets, however, bias can be introduced through the quality of images. For example, some demographics may have photos taken with lower quality equipment or with less diversity of lighting and environment conditions. This lack of diversity can reduce the model's ability to generalise and hence reduce race-based accuracy.

Further, our model was designed to classify attributes of individuals such as their race, age, and gender. However, these categories are not as granular as we'd like for real-world facial recognition UAV detection system. We chose to do this due to the time and resource constraints, as identity based facial recognition would require more resources than the compute on Google Collab could provide. Our testing should be explored on identity based facial recognition datasets using a dedicated GPU for training to address this. However, our findings are still valuable as they are directly applicable and transferable to this more complicated use case.

Hyperparameter optimisation should be further explored including algorithmic optimisation and epoch-based learning rate reductions. Additionally, the dataset still possesses a slight bias towards Caucasian people which can be improved by simply removing them, so each race has an equal amount of data. Moreover, our results and accuracy metrics could be visualised more intuitively with the implementation of a race-based confusion matrix.

Additionally, testing could be performed on other model architectures to quantify the impact of models on bias learning. Likewise, there are various algorithmic techniques which we revealed that are yet to be test. This includes adversarial learning which can reduce the impact of bias in situations where datasets cannot be modified. This is vital in population wide databases for government use. Moreover, this image alterations can be used to artificially inflate the dataset size. Some possible parameters to test include:

- rotation_range=45
- width_shift_range=0.2
- height_shift_range=0.2
- shear_range=0.2
- zoom_range=0.2
- horizontal_flip=True

Moreover, race and task specific models should be attempted to evaluate the impact on bias of this approach. Similarly, race specific accuracy metadata collection can be applied during training to update weights during training via penalisations of the loss function when the model exhibits bias. Finally, a cumulative approach using all of these techniques should be attempted to see if they have an additive effect.

VII. Conclusion

In conclusion our research has successfully addressed our research problem through the valid implementation of bias mitigation techniques. Our research revealed critical findings that fill significant gaps in the field. These findings are validated through reproducibility testing. Firstly, we demonstrated that augmenting datasets effectively reduces bias, as evidenced by a 25% improvement in accuracy. This underscores the importance of high-quality training data. We also found that hyperparameter optimisation significantly affects accuracy and loss. Our experiments showed that a learning rate of 0.001, 40 epochs, and a batch size of 32 yielded the highest accuracy of 0.94 on the test set.

Future research should address several limitations of our study. Algorithmic solutions to bias mitigation, combined with dataset augmentation could provide cumulative benefits. This is highly relevant to cases where dataset alterations are not possible, such as in real world surveillance contexts. Similarly, testing should be done on identity-based datasets for a more robust solution. Our findings and these further steps provide strong guidance for future research to address the concerns surrounding bias in UAV identification systems.

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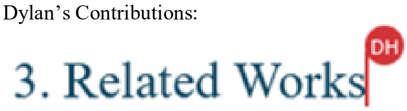
Appendix

[1] PowerPoint: https://studentutsedu-my.sharepoint.com/:p:/g/personal/william_sottoriva_student_uts_edu_au/EYrE6gcFPldJqsI7cWkn0aoBRt_X4xhx-BcQUW18k3ds0A?e=SRQQyL

[2] Code: https://drive.google.com/file/d/1eZKTy9vjPyLa3hTJMYL78XDapVuDFq4k/view?usp=sharing

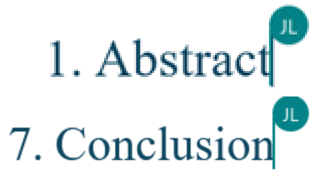
[3] Justin's Contributions:

[4] Dylan's Contributions:

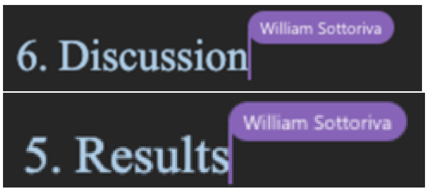


[5] Robert's Contributions:

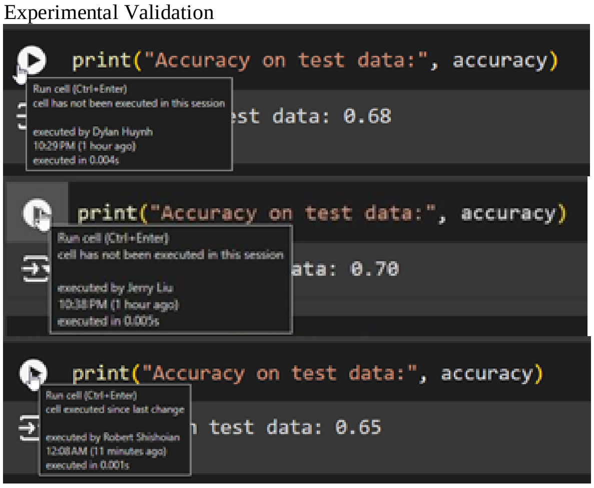
[6] Jerry's Contributions:



[7] William's Contributions:



[8] Experimental Validation



```
print("Accuracy on test data:", accuracy)
```

Run cell (Ctrl+Enter)
cell executed since last change

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executed in 0.321s

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ta: 0.75
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executed in 0.008s

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ta: 0.61
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print("Accuracy on test data:", accuracy)
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cell might have changed since last executed

executed by Justin Ngo
12:10AM (11 minutes ago)
executed in 0.005s

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data: 0.62
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[9] ResNet34 Architecture:

Model architecture:

Layer (type)	Output Shape	Param #
Conv2d-1	[-1, 64, 112, 112]	9,408
BatchNorm2d-2	[-1, 64, 112, 112]	128
ReLU-3	[-1, 64, 112, 112]	0
MaxPool2d-4	[-1, 64, 56, 56]	0
Conv2d-5	[-1, 64, 56, 56]	36,864
BatchNorm2d-6	[-1, 64, 56, 56]	128
ReLU-7	[-1, 64, 56, 56]	0
Conv2d-8	[-1, 64, 56, 56]	36,864
BatchNorm2d-9	[-1, 64, 56, 56]	128
ReLU-10	[-1, 64, 56, 56]	0
BasicBlock-11	[-1, 64, 56, 56]	0
Conv2d-12	[-1, 64, 56, 56]	36,864
BatchNorm2d-13	[-1, 64, 56, 56]	128
ReLU-14	[-1, 64, 56, 56]	0
Conv2d-15	[-1, 64, 56, 56]	36,864
BatchNorm2d-16	[-1, 64, 56, 56]	128
ReLU-17	[-1, 64, 56, 56]	0
BasicBlock-18	[-1, 64, 56, 56]	0
Conv2d-19	[-1, 64, 56, 56]	36,864
BatchNorm2d-20	[-1, 64, 56, 56]	128
ReLU-21	[-1, 64, 56, 56]	0
Conv2d-22	[-1, 64, 56, 56]	36,864
BatchNorm2d-23	[-1, 64, 56, 56]	128
ReLU-24	[-1, 64, 56, 56]	0
BasicBlock-25	[-1, 64, 56, 56]	0
Conv2d-26	[-1, 128, 28, 28]	73,728
BatchNorm2d-27	[-1, 128, 28, 28]	256
ReLU-28	[-1, 128, 28, 28]	0
Conv2d-29	[-1, 128, 28, 28]	147,456
BatchNorm2d-30	[-1, 128, 28, 28]	256
Conv2d-31	[-1, 128, 28, 28]	8,192
BatchNorm2d-32	[-1, 128, 28, 28]	256
ReLU-33	[-1, 128, 28, 28]	0
BasicBlock-34	[-1, 128, 28, 28]	0
Conv2d-35	[-1, 128, 28, 28]	147,456
BatchNorm2d-36	[-1, 128, 28, 28]	256
ReLU-37	[-1, 128, 28, 28]	0
Conv2d-38	[-1, 128, 28, 28]	147,456
BatchNorm2d-39	[-1, 128, 28, 28]	256
ReLU-40	[-1, 128, 28, 28]	0
BasicBlock-41	[-1, 128, 28, 28]	0
Conv2d-42	[-1, 128, 28, 28]	147,456
BatchNorm2d-43	[-1, 128, 28, 28]	256
ReLU-44	[-1, 128, 28, 28]	0
Conv2d-45	[-1, 128, 28, 28]	147,456
BatchNorm2d-46	[-1, 128, 28, 28]	256
ReLU-47	[-1, 128, 28, 28]	0
BasicBlock-48	[-1, 128, 28, 28]	0
Conv2d-49	[-1, 128, 28, 28]	147,456
BatchNorm2d-50	[-1, 128, 28, 28]	256
ReLU-51	[-1, 128, 28, 28]	0
Conv2d-52	[-1, 128, 28, 28]	147,456
BatchNorm2d-53	[-1, 128, 28, 28]	256
ReLU-54	[-1, 128, 28, 28]	0
BasicBlock-55	[-1, 128, 28, 28]	0
Conv2d-56	[-1, 256, 14, 14]	294,912
BatchNorm2d-57	[-1, 256, 14, 14]	512
ReLU-58	[-1, 256, 14, 14]	0
Conv2d-59	[-1, 256, 14, 14]	589,824
BatchNorm2d-60	[-1, 256, 14, 14]	512
Conv2d-61	[-1, 256, 14, 14]	32,768
BatchNorm2d-62	[-1, 256, 14, 14]	512
ReLU-63	[-1, 256, 14, 14]	0
BasicBlock-64	[-1, 256, 14, 14]	0
Conv2d-65	[-1, 256, 14, 14]	589,824
BatchNorm2d-66	[-1, 256, 14, 14]	512
ReLU-67	[-1, 256, 14, 14]	0
Conv2d-68	[-1, 256, 14, 14]	589,824
BatchNorm2d-69	[-1, 256, 14, 14]	512
ReLU-70	[-1, 256, 14, 14]	0
BasicBlock-71	[-1, 256, 14, 14]	0
Conv2d-72	[-1, 256, 14, 14]	589,824
BatchNorm2d-73	[-1, 256, 14, 14]	512
ReLU-74	[-1, 256, 14, 14]	0
Conv2d-75	[-1, 256, 14, 14]	589,824
BatchNorm2d-76	[-1, 256, 14, 14]	512
ReLU-77	[-1, 256, 14, 14]	0
BasicBlock-78	[-1, 256, 14, 14]	0
Conv2d-79	[-1, 256, 14, 14]	589,824
BatchNorm2d-80	[-1, 256, 14, 14]	512
ReLU-81	[-1, 256, 14, 14]	0
Conv2d-82	[-1, 256, 14, 14]	589,824
BatchNorm2d-83	[-1, 256, 14, 14]	512
ReLU-84	[-1, 256, 14, 14]	0
BasicBlock-85	[-1, 256, 14, 14]	0
Conv2d-86	[-1, 256, 14, 14]	589,824
BatchNorm2d-87	[-1, 256, 14, 14]	512
ReLU-88	[-1, 256, 14, 14]	0
Conv2d-89	[-1, 256, 14, 14]	589,824
BatchNorm2d-90	[-1, 256, 14, 14]	512
ReLU-91	[-1, 256, 14, 14]	0
BasicBlock-92	[-1, 256, 14, 14]	0
Conv2d-93	[-1, 256, 14, 14]	589,824
BatchNorm2d-94	[-1, 256, 14, 14]	512
ReLU-95	[-1, 256, 14, 14]	0
Conv2d-96	[-1, 256, 14, 14]	589,824
BatchNorm2d-97	[-1, 256, 14, 14]	512
ReLU-98	[-1, 256, 14, 14]	0
BasicBlock-99	[-1, 256, 14, 14]	0
Conv2d-100	[-1, 512, 7, 7]	1,179,648
BatchNorm2d-101	[-1, 512, 7, 7]	1,024
ReLU-102	[-1, 512, 7, 7]	0
Conv2d-103	[-1, 512, 7, 7]	2,359,296
BatchNorm2d-104	[-1, 512, 7, 7]	1,024
Conv2d-105	[-1, 512, 7, 7]	131,072
BatchNorm2d-106	[-1, 512, 7, 7]	1,024
ReLU-107	[-1, 512, 7, 7]	0
BasicBlock-108	[-1, 512, 7, 7]	0
Conv2d-109	[-1, 512, 7, 7]	2,359,296
BatchNorm2d-110	[-1, 512, 7, 7]	1,024
Conv2d-112	[-1, 512, 7, 7]	2,359,296
BatchNorm2d-113	[-1, 512, 7, 7]	1,024
ReLU-114	[-1, 512, 7, 7]	0
BasicBlock-115	[-1, 512, 7, 7]	0
Conv2d-116	[-1, 512, 7, 7]	2,359,296
BatchNorm2d-117	[-1, 512, 7, 7]	1,024
ReLU-118	[-1, 512, 7, 7]	0
Conv2d-119	[-1, 512, 7, 7]	2,359,296
BatchNorm2d-120	[-1, 512, 7, 7]	1,024
ReLU-121	[-1, 512, 7, 7]	0
BasicBlock-122	[-1, 512, 7, 7]	0
AdaptiveAvgPool2d-123	[-1, 512, 1, 1]	0
Linear-124	[-1, 18]	9,234

Total params: 21,293,906
Trainable params: 21,293,906
Non-trainable params: 0

Input size (MB): 0.57
Forward/backward pass size (MB): 96.28
Params size (MB): 81.23
Estimated Total Size (MB): 178.09