CNN Report

Introduction:

Artificial Intelligence is rapidly being employed in many areas of human endeavour. Deep learning (DL) is used the ability to learn robust representation from image and convolutional neural network (CNN) is the principal DL architecture employed for image classification. As against other traditional DL architectures, it makes use of convolutional operations in at least one of it layers (Russell and Norvig, 2021). It operates on layered abstraction, the lower the level of abstraction, the more detail. It finds use also in text recognition, security and surveillance, etc. It has its origin in the work of David Hubel and Torsten Wiesel in 1959.

Architecture of CNN

1. **Filter bank or kernels:** each filter or kernel aims to detect a particular characteristic at each input location.
2. **Convolution layer:** the convolution operation is widely used in digital image processing where the 2D matrix representing the image (I) is convolved with the smaller 2D kernel matrix (K), then the mathematical formulation with zero padding This is the most important layer of the CNN architecture.
3. **Nonlinear activation function:** after the filter bank produces the output, a nonlinear activation function is applied (Equation (1)) to produce the activation maps, where only the activated features are carried forward to the next layer.
4. **Pooling layer:** it reduces the number of parameters of the network by reducing the spatial size of convolutional outputs. (Naranjo-Torres et at, 2020)

Project Goal:

The aim of this paper is to develop a Convolutional Neural Network (CNN) model to identify species of flowers from photographs. The dataset is tf_flowers dataset from Tensor Flow. It c ontains 3670 colour photographs of flowers, consisting of five different species: daisy', 'dand elion', 'roses', 'sunflowers', 'tulips. Our goal is to tune to get a model with an accuracy near to 1.

Data Preprocessing

This is a cleaned dataset and we have no need for data cleaning. We proceeded to import nec essary libraries and pointed to the dataset and then went ahead to load the datatset to comm ence processing

Model 1

This first model was trained at with a learning rate of .001 and a batch size of 32. Other parameters are summarized below:

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 254, 254, 32)      896

 max_pooling2d (MaxPooling2  (None, 127, 127, 32)      0
 D)

 conv2d_1 (Conv2D)           (None, 125, 125, 64)      18496

 max_pooling2d_1 (MaxPoolin  (None, 62, 62, 64)        0
 g2D)

 conv2d_2 (Conv2D)           (None, 60, 60, 128)       73856

 max_pooling2d_2 (MaxPoolin  (None, 30, 30, 128)       0
 g2D)

 flatten (Flatten)           (None, 115200)            0

 dense (Dense)               (None, 64)                7372864

 dropout (Dropout)           (None, 64)                0

 dense_1 (Dense)             (None, 5)                 325

=================================================================
Total params: 7466437 (28.48 MB)
Trainable params: 7466437 (28.48 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

After training, I got the following result:

```
              precision    recall  f1-score   support

           0       0.66      0.80      0.72        50
           1       0.77      0.76      0.76        91
           2       0.69      0.72      0.71        68
           3       0.76      0.91      0.83        70
           4       0.82      0.57      0.67        88

    accuracy                           0.74       367
   macro avg       0.74      0.75      0.74       367
weighted avg       0.75      0.74      0.74       367
```

The accuracy of this training is 0.74.

This also shows in the training and validation sets versus epoch

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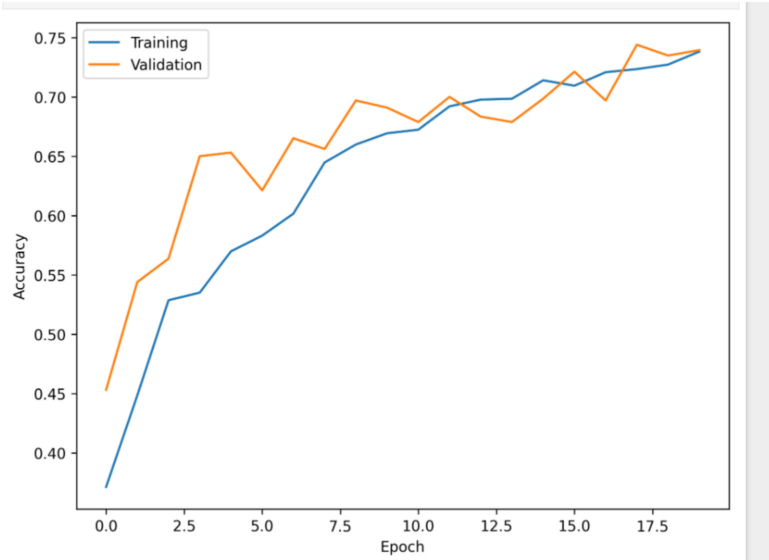
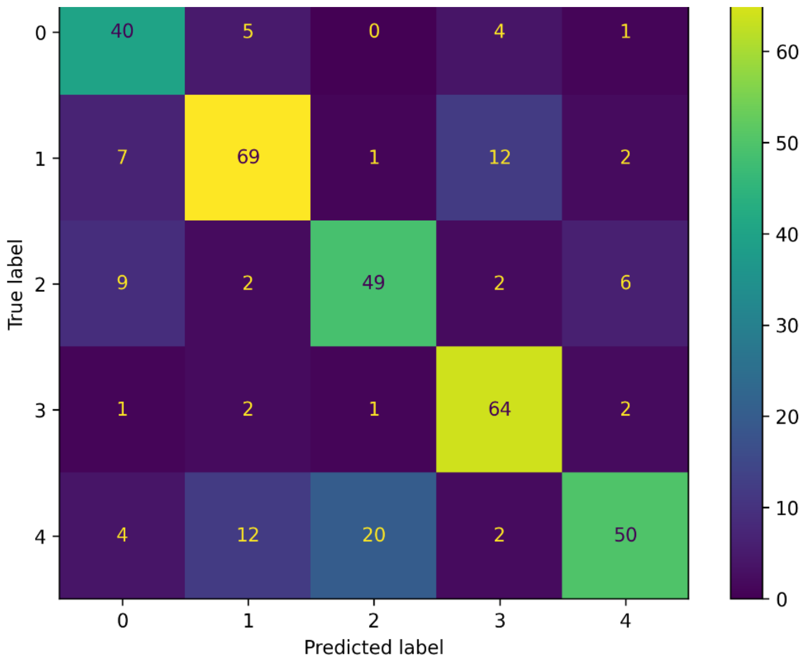


Finally, I plotted a confusion matrix. A confusion matrix shows which class labels are easier to predict than others. In this case, dandelion is the easiest to predict and roses the least.

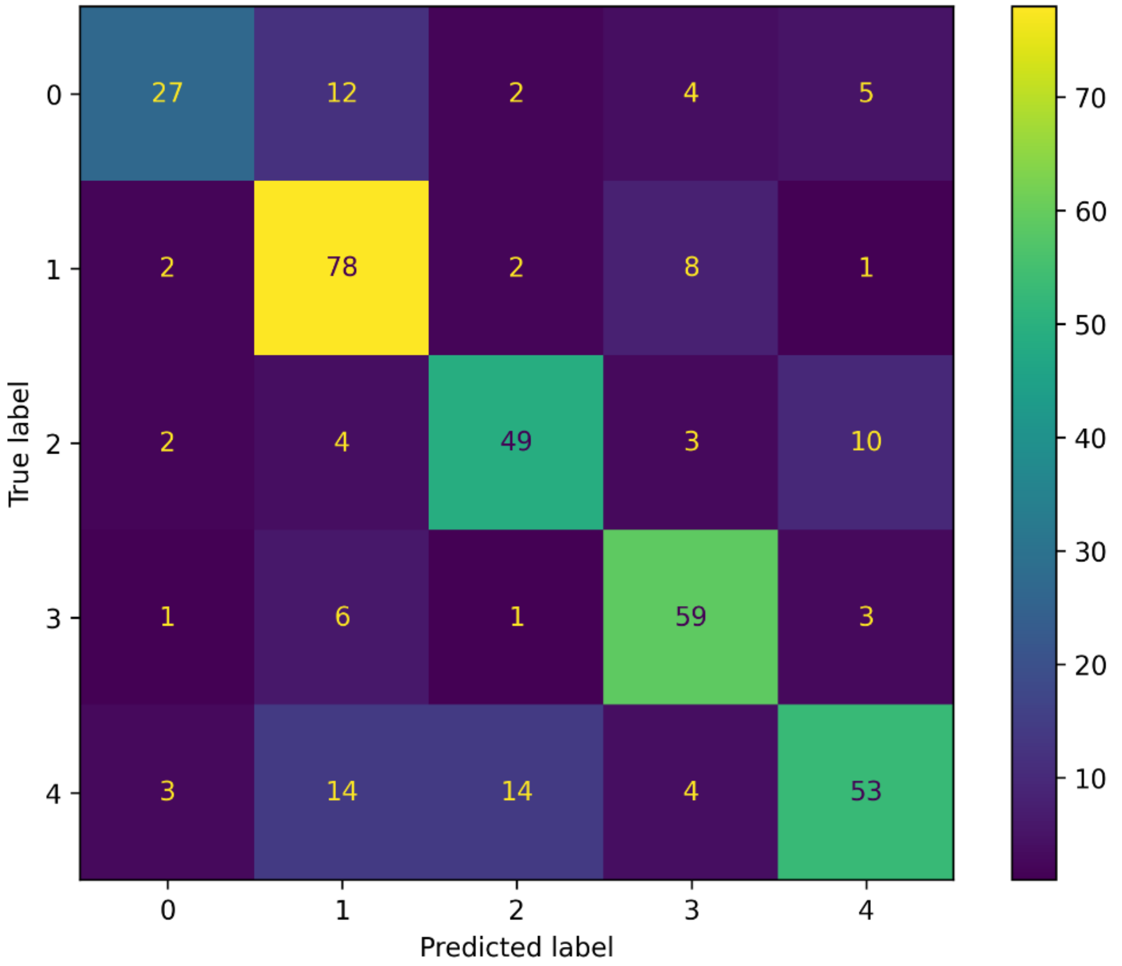


Model 2: Batch size from 32 to 64

This model reduced the final accuracy from .74 to .72

	precision	recall	f1-score	support
0	0.77	0.54	0.64	50
1	0.68	0.86	0.76	91
2	0.72	0.72	0.72	68
3	0.76	0.84	0.80	70
4	0.74	0.60	0.66	88
accuracy			0.72	367
macro avg	0.73	0.71	0.72	367
weighted avg	0.73	0.72	0.72	367

Dandelion is still the easiest to recognize



Model 3:

I maintained the batch size at 64 and increased the kernel size from (3,3) to (5,5) but this accuracy stayed at .72

	precision	recall	f1-score	support
0	0.77	0.54	0.64	50
1	0.68	0.86	0.76	91
2	0.72	0.72	0.72	68
3	0.76	0.84	0.80	70
4	0.74	0.60	0.66	88
accuracy			0.72	367
macro avg	0.73	0.71	0.72	367
weighted avg	0.73	0.72	0.72	367

Model 4: Increase the Stride Length on the Conv2D Layers to 2

I reverted to batch size of 32 and increased the Stride Length on the Conv2D Layers to 2. The final accuracy improved from .74 of Model 1 to .75. Increase in batch size and kernel size made no improvement; batch size even reduced out accuracy score

Model 5: Changing Maxpooling to Avgpooling

To Model 4 above,I changed Maxpooling to Avgpooling. This reduced our score from .75 to .71

	precision	recall	f1-score	support
0	0.74	0.84	0.79	50
1	0.69	0.80	0.74	91
2	0.65	0.66	0.66	68
3	0.74	0.86	0.79	70
4	0.78	0.48	0.59	88
accuracy			0.71	367
macro avg	0.72	0.73	0.71	367
weighted avg	0.72	0.71	0.71	367

Model 6: Introducing Batch Normalisation

To Model 4, I introduced Model 6: batch normalisation and the accuracy stayed below .75 at 0.73. Batch normalization helps the network to converge faster and reduces dependencies on hyper-parameters.

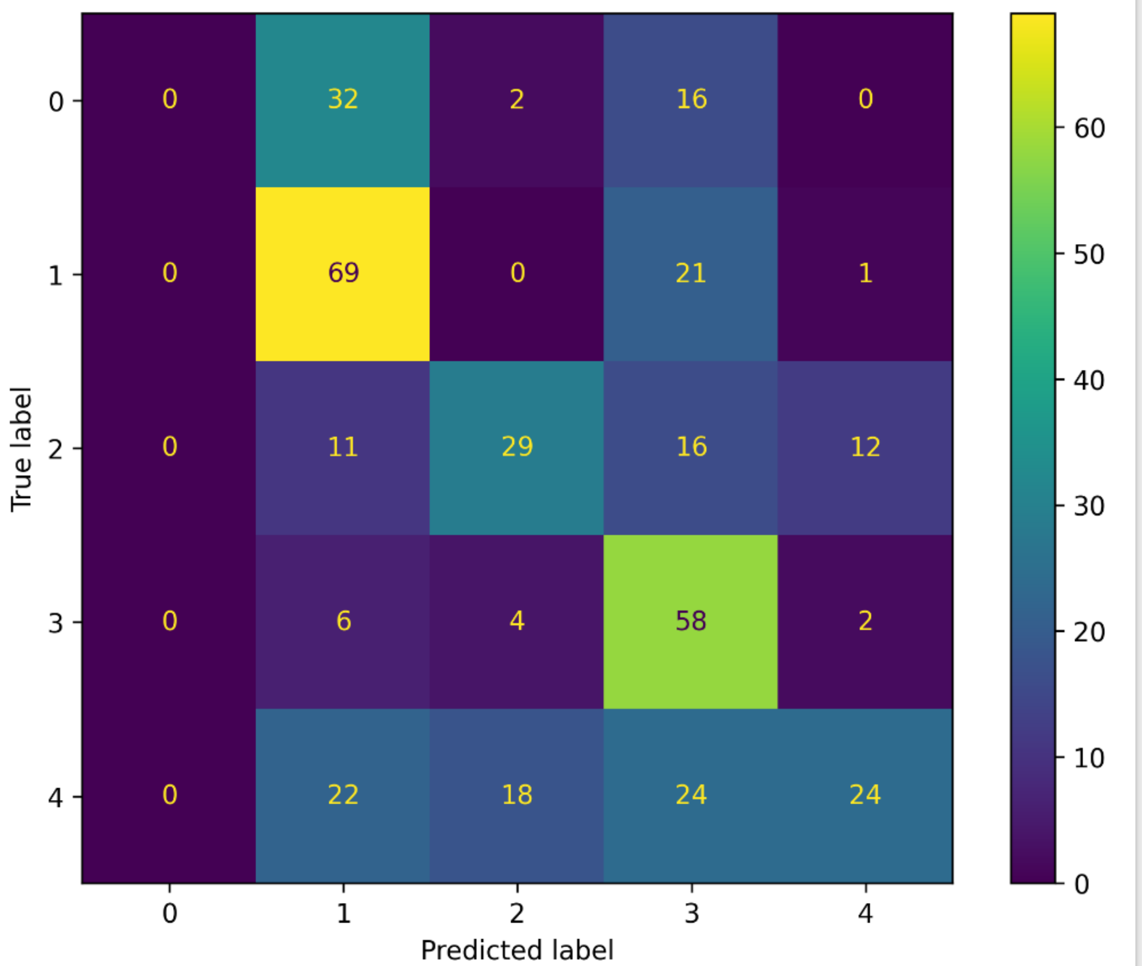
	precision	recall	f1-score	support
0	0.73	0.80	0.76	50
1	0.72	0.82	0.77	91
2	0.76	0.57	0.66	68
3	0.87	0.64	0.74	70
4	0.65	0.77	0.70	88
accuracy			0.73	367
macro avg	0.75	0.72	0.73	367
weighted avg	0.74	0.73	0.73	367

Model 7: Increasing the learning rate from .001 to .01

Increasing the learning rate gave us a very poor accuracy score of .49

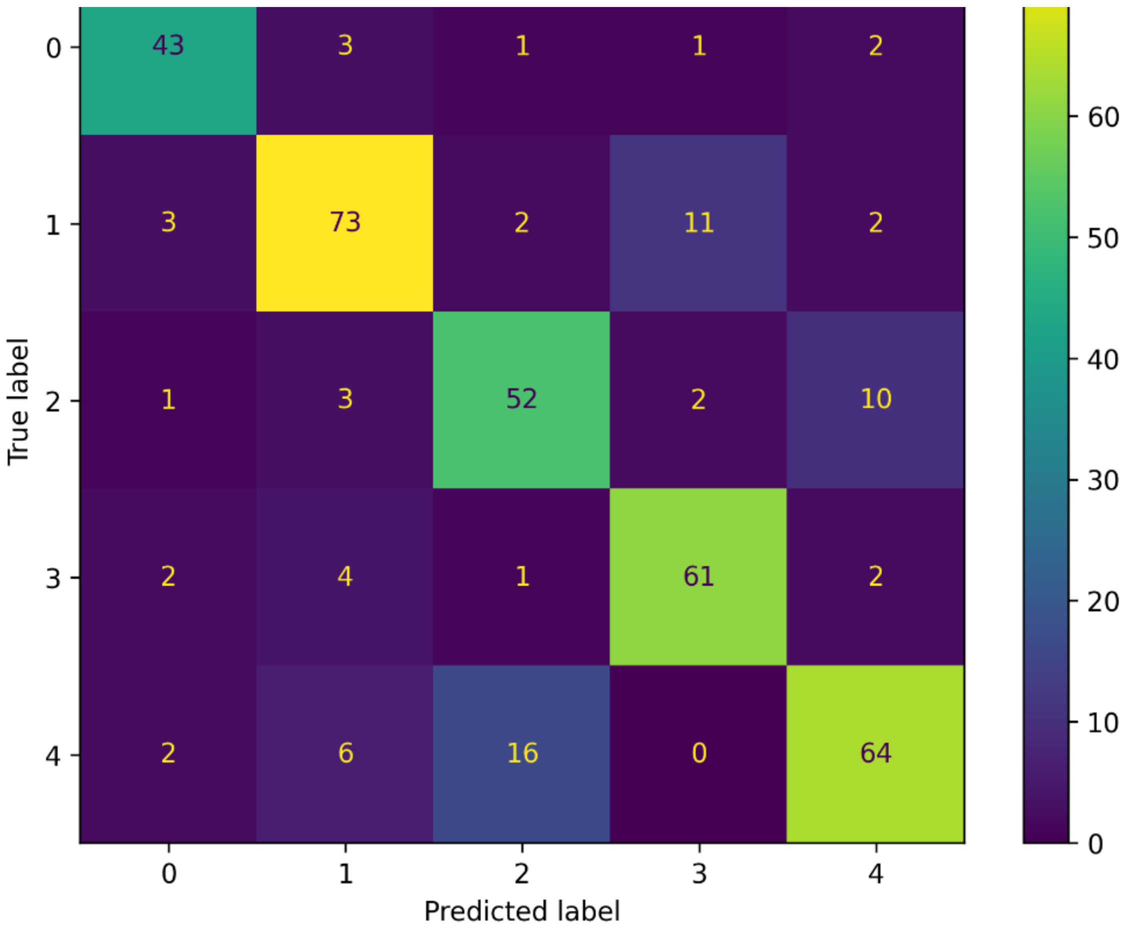
	precision	recall	f1-score	support
0	0.00	0.00	0.00	50
1	0.49	0.76	0.60	91
2	0.55	0.43	0.48	68
3	0.43	0.83	0.57	70
4	0.62	0.27	0.38	88
accuracy			0.49	367
macro avg	0.42	0.46	0.40	367
weighted avg	0.45	0.49	0.44	367

Up to this moment, the confusion matrix has only changed marginally even with a low accuracy of .49



Model 8: Increasing the number of epochs by 50% (20 - 40)

I tweaked our Model 4 by increasing the number of epochs by 50% and it paid off as accuracy increased to .8

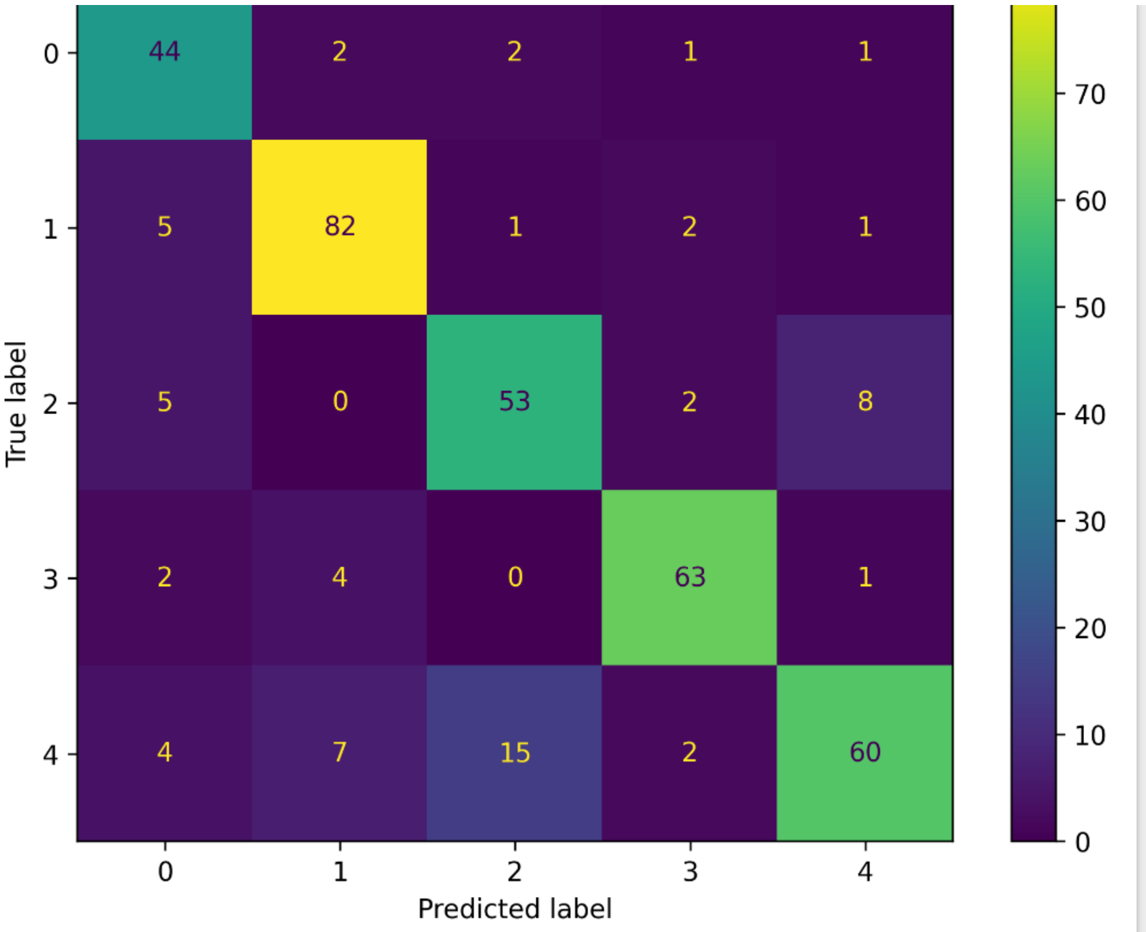


	precision	recall	f1-score	support
0	0.84	0.86	0.85	50
1	0.82	0.80	0.81	91
2	0.72	0.76	0.74	68
3	0.81	0.87	0.84	70
4	0.80	0.73	0.76	88
accuracy			0.80	367
macro avg	0.80	0.81	0.80	367
weighted avg	0.80	0.80	0.80	367

Model 9: Taking the Number of epoch to 100 and adding EarlyStopping

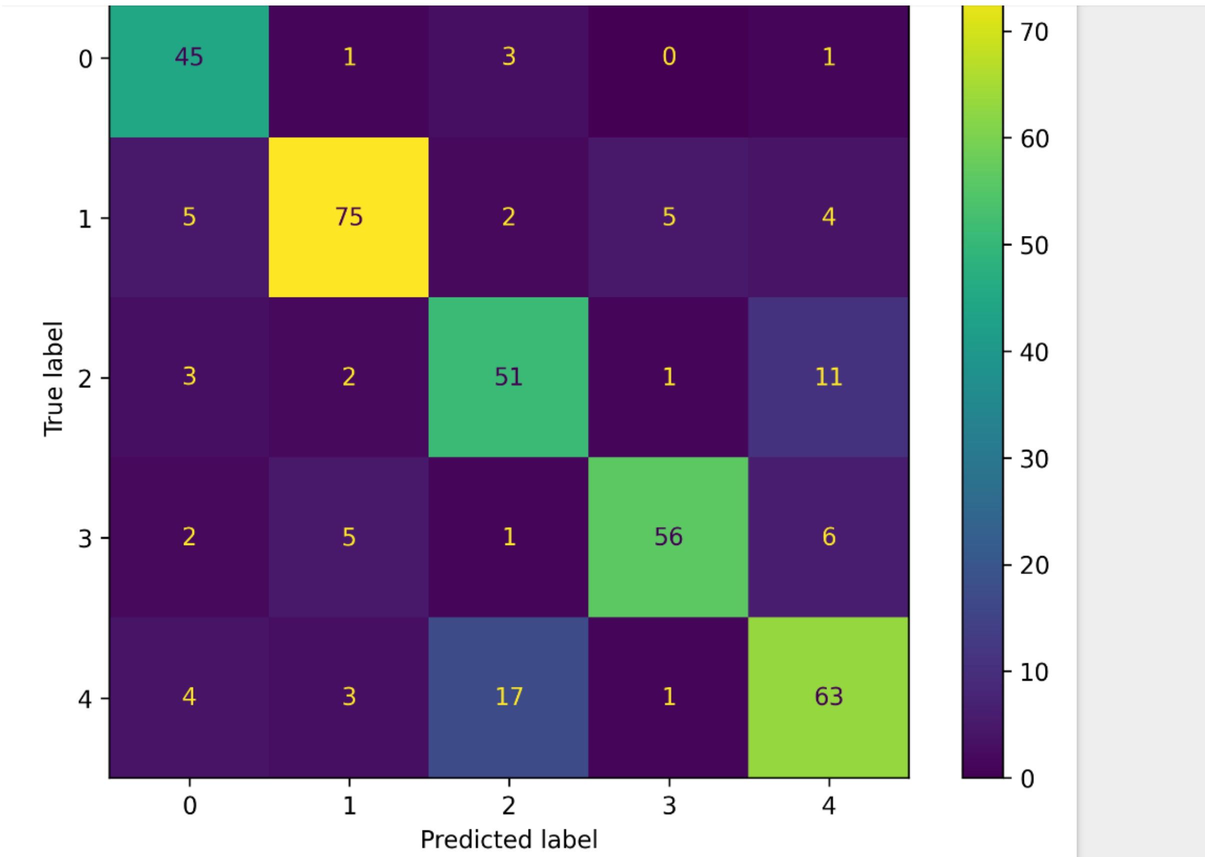
I further increased the number of epochs and took it 100. It returned an accuracy of .82 and did not stop early and I wanted to confirm that there cannot be a epoch value lesser than 100 that will give us a higher accuracy

	precision	recall	f1-score	support
0	0.73	0.88	0.80	50
1	0.86	0.90	0.88	91
2	0.75	0.78	0.76	68
3	0.90	0.90	0.90	70
4	0.85	0.68	0.75	88
accuracy			0.82	367
macro avg	0.82	0.83	0.82	367
weighted avg	0.83	0.82	0.82	367



Model 9: Brining down the Number of epoch 100 from 100 to 50

	precision	recall	f1-score	support
0	0.76	0.90	0.83	50
1	0.87	0.82	0.85	91
2	0.69	0.75	0.72	68
3	0.89	0.80	0.84	70
4	0.74	0.72	0.73	88
accuracy			0.79	367
macro avg	0.79	0.80	0.79	367
weighted avg	0.80	0.79	0.79	367



Conclusion

Model 9 with the higher recorded accuracy of .82 is the best model here and this is followed by followed by Model 8 with accuracy of.80. To improve this model further, I would need to increase the number of epoch and as the number of epochs affect the performance. For large number of epochs , there is improvement in performance but there is to do certain experimentation for deciding epochs, learning rate (https://medium.com/,2024) . In this project, I have demonstrated that the decreasing the learning rate has negative effect on accuracy as well as reducing the number of epochs from 100 to 50 although we saw that 40 epoch gave better accuracy of .80 as against .79 of 50 but this difference is not so much as to negate our view that a training our model with epochs higher than 100 will bring better result. Our CNN model to ide ntified ‘1:dandelion’ best from photographs in comparison to the other flowers. CNN is a pilla r algorithm of deep learning and has proven useful in many areas like computer vision and it is leading the self-driving car innovation. More research development works needs to be focu sed on CNN by scholars and AI professionals to improves its accuracy and help life in the soc iety including health and agriculture.

References:

Naranjo-Torres, J.; Mora, M.; Hernández-García, R.; Barrientos, R.J.; Fredes, C.; Valenzuela, A. A Review of Convolutional Neural Network Applied to Fruit Image Processing. *Appl. Sci.* **2020**, *10*, 3443. https://doi.org/10.3390/app10103443

Russell,S. and Norvig,P., (2021).Artificial intelligence: a modern approach, 4th Ed. Pearson, Harlow

https://medium.com/ (2024), Improving Performance of Convolutional Neural Network! | by Dipti Pawar | Medium

Literature Review on Ethical Implication of Artificial intelligence (AI)

This presentation is a review of three literatures on bias in AI. AI based system are today used in most industries and there are debates on whether AI will replace us in many fields (Karta, 2023). The implication of a biased AI system are severe as seen in the COMPAS system used in the US criminal justice system for predicting the risk of re-offending defendants which scores blacks more than their actual risks (Ntoutsi,2019) and in minority borrowers paying higher interest rate on loans (Pessach and Shmueli,2021). The papers trace the origin of the bias and proffer solutions on how to mitigate bias in AI.

In their work, Ntoutsi et al. (2019) presented a multidisciplinary overview of the areas of bias in AI systems. This group of twenty-three scholars argue that given that AI relies heavily on data generated by humans, biases that exist in humans pass into our systems and AI systems can magnify historical biases. They hold that AI algorithms should incorporate ethical and legal principles in their design, training, and deployment. For them, AI systems without social and legal footings cannot stand, and they advocate that AI bias should not be approached as only a technical enterprise and recommend a multidisciplinary approach.

On the other hand, Pessach and Shmueli (2021) examined the fairness of AI algorithms in data settings where unprivileged groups are not equally represented as compared to their privileged counterparts. They argue that this selection bias can lead to a high algorithmic bias and their work demonstrated with a hands-on project on ways to eliminate bias in AI systems. They concluded that adaptations to in-process and pre-process fairness mechanisms alongside both supervised and semi-supervised learning algorithms can greatly improve fairness considerably with marginal compromise in accuracy.

Karta (2023) aimed at raising awareness of AI bias among researchers and examined bias in the decision-making process of AI systems and the factors that lead to bias in AI systems. and then allayed fears by proffering steps to mitigate bias in AI systems. The paper concludes that the elimination of bias from AI is a sociotechnical issue and recommends interdisciplinary studies with the contribution of sociology, psychology, and computer sciences.

Overall, all three articles acknowledge the existence of bias in AI system and that bias can be traced to the data presented to the system during the training phase. While Pessach and Shmueli (2021) argue that proponents of the view that AI algorithms are free from biases are wrong for several reasons, Karta (2023) holds that because it is impossible to eliminate bias in humans, a completely neutral AI system is not possible and she agrees with Ntoutsi et al. (2019) that effects of the bias can be mitigated.

Ntoutsi et al. (2019) presented 3 stages where mitigation action can be carried out to minimize bias: preprocessing (producing a balanced dataset that can be presented to the system), in-processing stage that includes training on latent target labels, and post-processing (processing the classification model after it has been learned from data). Karta (2023) concurs with these three approaches but was more detailed on activities that can be performed under each approach. On the other hand, Pessach and Shmueli (2021) advocated mitigation of bias via pre-process fairness mechanism, and in-process mechanisms based on supervised learning algorithms to optimize accuracy using only labelled data of the privileged group. To optimize accuracy, they suggest a pre-process and an in-process mechanisms based on a semi-supervised learning algorithm which uses unlabelled data of the unprivileged group.

Ntoutsi et al. (2019) and Karta (2023) are agreed that the challenge of bias should not be addressed in silos but rather given a multidisciplinary approach.

Pessach and Shmueli (2021) were more practical in their presentation and the mitigation steps they advocated were arrived at from their hands-on experiment. While Karta (2023) advocates that academic institutions should incorporate bias in their syllables, Ntoutsi et al. (2019) argue that the application of data anti-discrimination laws among others to AI are unclear and they advocate that further work needs to be done on legal framework governing AI.

Three Successes

1. AI Fairness 360 by IBM is used to mitigate bias in datasets and models
2. Fairlearn by Microsoft identifies biases that affect people and is employed to eliminate bias in recruitment, bank lending, admissions into colleges, etc.
3. FairML probes various types of bias in predictive model to ascertain the extent of fairness of a model.

Three Challenges

1. Absence of adequate legislation
2. Lack of multidisciplinary cooperation in tackling AI bias
3. Inadequate training of AI practitioners on managing bias

Three Suggestions

1. There is need for adequate legislation that will provide a comprehensive legal framework governing more areas of AI systems including provision for approval by a regulator before system deployment.
2. Given that issues like bias are not purely technical problems, there is need for frank engagement with other disciplines including but not limited to social sciences
3. AI practitioners will need more training to appreciate that fair algorithms in AI systems will bring about a safer world as issues of discrimination may in some cases lead to violent extremism by the disadvantaged group.

In conclusion, I find the multidisciplinary approach as a veritable approach to minimizing if not eradicating bias in AI. There is a strong need for an expanded legislation that will, among other things, establish a regulator that will vet AI systems for absence of bias before release. AI practitioners should always ensure that input datasets fairly represent the population for which a model is being designed. In extreme circumstances where only historically biased datasets are available, steps should be taken at the preprocessing stage to eliminate these biases before these datasets are presented to the system.

References

Kartal, E., (2022). A Comprehensive Study on Bias in Artificial Intelligence Systems: Biased or Unbiased AI, That's the Question! *International Journal of Intelligent Information Technologies,* Volume 18(1). Available on: https://orcid.org/0000-0003-4667-1806 [Accessed 29/12/2023].

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Pessach, D., & Shmueli, E. (2021). Improving fairness of artificial intelligence algorithms in Privileged-Group Selection Bias data settings, *Expert Systems with Applications*, 185. Available online: https://doi.org/10.1016/j.eswa.2021.115667 [Accessed 27/12/2023].