King Abdulaziz University
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EYEQ

Eye Disease Classification Assignment

CPCS_432

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Contents

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3.Project Name and Proposal Paragraph:

Project Name: EyeQ

Proposal Paragraph:

Eye diseases, including Glaucoma, Myopia, Cataract, Diabetic Retinopathy, and Macular Scar, are major causes of disability worldwide, significantly affecting populations in countries like Bangladesh, where 1.5% of adults are blind and 21.6% suffer from low vision. Early detection is crucial to prevent vision loss. EyeQ, an AI project, uses computer vision to classify retinal images, helping healthcare providers make faster and more accurate diagnoses for better patient outcomes.

4.Dataset Description:

We used two datasets, each containing multiple classes. Each member of the group worked on classifying a specific disease along with the Healthy class. The datasets used are.

Dataset 01

This eye disease dataset, collected from sources like Anwara Hamida Eye Hospital and BNS Zahrul Haque Eye Hospital in Bangladesh, is crucial for advancing research in nonfatal disabling conditions affecting vision. It contains 5,335 original and 16,242 augmented retinal images, representing both healthy and diseased eyes across various conditions such as

Diabetic Retinopathy, Cataract, Glaucoma, Retinitis Pigmentosa, and Macular Scar (Riadur Rashid, Sharmin, Khatun, Hasan, & Shorif Uddin, 2024).

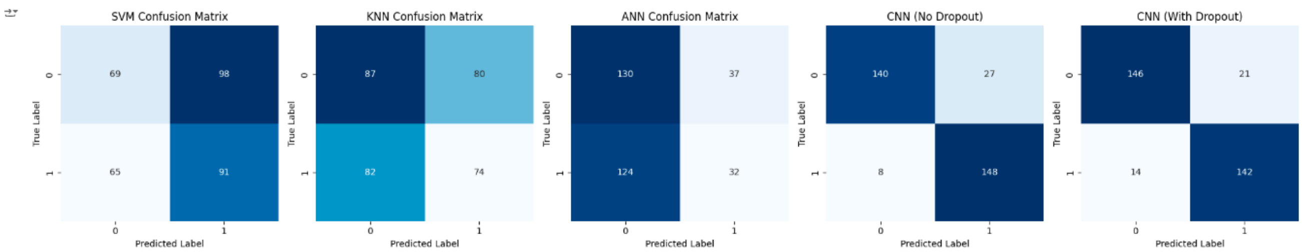
Dataset 02

The dataset comprises retinal images categorized into four classes: Normal, Diabetic Retinopathy, Cataract, and Glaucoma, with approximately 1,000 images in each class. These images have been carefully sourced from various datasets, including IDRiD, Ocular Recognition, and HRF, to ensure diversity and accuracy in data representation images have been carefully sourced from various datasets, including IDRiD, Ocular Recognition, and HRF, .to ensure diversity and accuracy in data representation (Doddi, 2022).

I used the first dataset and selected the Glaucoma class, with a total of 1600 images. My classification focused on identifying whether the condition was Glaucoma or Health.

5.Comparison of Classical and CNN Methods

5.1Confusion Matrices



SVM Confusion Matrix:

True positives (TP): 69

False negatives (FN): 65

False positives (FP): 98

True negatives (TN): 91

This model shows a moderate number of correctly predicted labels, but the relatively high number of false positives (98) indicates it struggles with over-predicting one class.

KNN Confusion Matrix:

TP: 87

FN: 82

FP: 80

TN: 74

KNN has a more balanced distribution of correct and incorrect predictions compared to SVM but still shows a significant number of both false positives and false negatives.

ANN Confusion Matrix:

TP: 130

FN: 124

FP: 37

TN: 32

ANN performs better in terms of true positives, but it has a large number of false negatives, showing that it might struggle with one class more than the other.

CNN (No Dropout) Confusion Matrix:

TP: 140

FN: 8

FP: 27

TN: 148

The CNN without dropout performs significantly better than the previous models, with high true positive and true negative counts and relatively low false positive and false negative counts.

CNN (With Dropout) Confusion Matrix:

TP: 146

FN: 14

FP: 21

TN: 142

The CNN with dropout performs very similarly to the one without dropout but with slightly higher true positive and true negative counts. The inclusion of dropout likely helps prevent overfitting while maintaining strong performance.

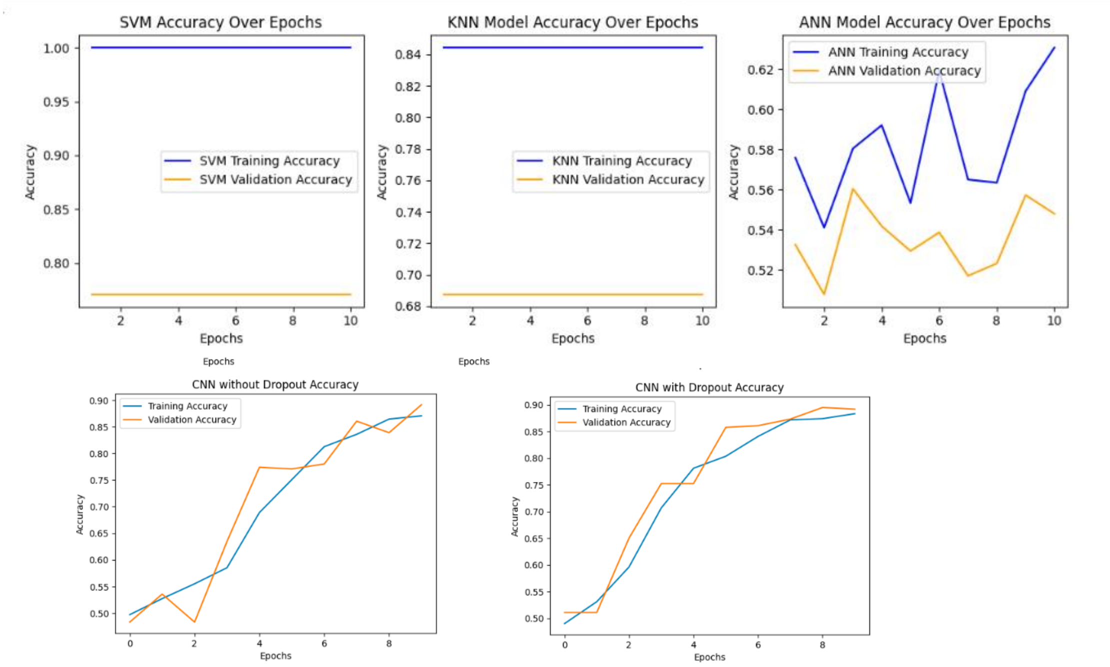
Comparison:

SVM and KNN models show weaker performance compared to the neural network-based models. Both models have higher false positives and false negatives.

ANN shows improved true positive counts but suffers from a large number of false negatives, suggesting it may need further optimization.

CNN models perform the best, with the CNN with dropout marginally outperforming the one without dropout. Dropout helps the model generalize better, as seen in the reduced number of false positives and false negatives compared to the other models.

5.2.Training Curves



SVM Model

The SVM model shows a perfect training accuracy (potentially indicating overfitting), while the validation accuracy stays much lower and flat, suggesting that the model may not generalize well.

KNN Model

The gap between training and validation accuracy points to a possible overfitting issue. The model's performance does not improve over epochs, indicating it might not benefit from further training iterations.

ANN Model

This model appears to have a significant difference between training and validation accuracy, suggesting that it may be overfitting. However, the fluctuations in training accuracy indicate that the model could benefit from further optimization, such as tuning hyperparameters or using regularization techniques.

Overall Comparison:

SVM shows the highest training accuracy but with potential overfitting since the validation accuracy remains significantly lower.

KNN also demonstrates overfitting, with a consistent training accuracy higher than the validation accuracy.

ANN exhibits more dynamic behavior, suggesting potential underfitting or overfitting due to fluctuating validation accuracy. This model may need further tuning to improve both training and validation performance.

CNN without Dropout:

The training and validation accuracies are closely aligned. This suggests that the model without dropout can achieve high performance than classical models .

CNN with Dropout

The dropout mechanism helps prevent overfitting by regularizing the model. The similar final accuracies for training and validation indicate that the dropout effectively maintains the model's generalization.

Comparison with Previous Models (SVM, KNN, ANN):

Performance Stability:

The CNN models (both with and without dropout) show a stable improvement in both training and validation accuracies over the epochs, contrasting with the SVM and KNN models, which had relatively flat training and validation accuracies.

The ANN model had fluctuating accuracies and did not exhibit a consistent upward trend, whereas the CNN models present a steady increase, suggesting a more effective learning process.

Overfitting and Generalization:

The CNN without dropout has closely matched training and validation curves, indicating minimal overfitting. However, introducing dropout further ensures that overfitting is controlled.

In comparison, the SVM and KNN models show signs of overfitting, with training accuracies significantly higher than their validation accuracies.

The ANN model also displayed a significant gap between training and validation accuracies, suggesting overfitting.

Effectiveness of Dropout:

The bottom plot (CNN with dropout) confirms the effectiveness of dropout in reducing overfitting. The consistent alignment between training and validation accuracies suggests that dropout helps maintain generalization.

Neither the SVM, KNN, nor ANN plots involved regularization techniques like dropout, which might explain their more pronounced overfitting issues.

5.3.Analysis of Classification Reports

```
SVM Classification Report:
              precision    recall  f1-score   support

           0       0.83      0.69      0.75       162
           1       0.73      0.86      0.79       161

    accuracy                           0.77       323
   macro avg       0.78      0.77      0.77       323
weighted avg       0.78      0.77      0.77       323

KNN Classification Report:
              precision    recall  f1-score   support

           0       0.68      0.71      0.69       162
           1       0.69      0.66      0.68       161

    accuracy                           0.69       323
   macro avg       0.69      0.69      0.69       323
weighted avg       0.69      0.69      0.69       323

ANN Classification Report:
              precision    recall  f1-score   support

           0       0.53      0.83      0.65       162
           1       0.61      0.26      0.37       161

    accuracy                           0.55       323
   macro avg       0.57      0.55      0.51       323
weighted avg       0.57      0.55      0.51       323
```

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11/11 ━━━━━━━━━━━━━━━━━━━━ 6s 496ms/step
CNN without Dropout Classification Report:
              precision    recall  f1-score   support

           0       0.95      0.84      0.89       167
           1       0.85      0.95      0.89       156

    accuracy                           0.89       323
   macro avg       0.90      0.89      0.89       323
weighted avg       0.90      0.89      0.89       323

11/11 ━━━━━━━━━━━━━━━━━━━━ 8s 712ms/step
CNN with Dropout Classification Report:
              precision    recall  f1-score   support

           0       0.91      0.87      0.89       167
           1       0.87      0.91      0.89       156

    accuracy                           0.89       323
   macro avg       0.89      0.89      0.89       323
weighted avg       0.89      0.89      0.89       323
```

SVM Classification Report:

Overall Accuracy: 0.77

The SVM model has a decent balance between precision and recall, but the performance for Class 0 is weaker compared to Class 1, indicating potential bias in classifying Class 0 instances.

KNN Classification Report:

Overall Accuracy: 0.69

The KNN model shows balanced metrics between the two classes but with overall lower precision, recall, and f1-scores compared to SVM. The performance is similar across both classes, indicating that the model struggles with both equally.

ANN Classification Report:

Overall Accuracy: 0.55

The ANN model's performance is notably poorer, especially for Class 1, which has a very low recall (0.26). This indicates that the ANN model struggles significantly in identifying Class 1 instances and might need substantial tuning.

CNN without Dropout Classification Report:

Overall Accuracy: 0.89

The CNN model without dropout performs significantly better than the SVM, KNN, and ANN models. It achieves high precision, recall, and f1-scores for both classes.

CNN with Dropout Classification Report:

Overall Accuracy: 0.89

The CNN with dropout also performs very well, with slightly better balance between precision and recall compared to the CNN without dropout. This indicates that dropout helps maintain high performance while controlling overfitting.

5.Reference

Doddi, G. V. (2022). Retrieved from https://www.kaggle.com/datasets/gunavenkatdoddi/eye-diseases-classification/data.

Riadur Rashid, M., Sharmin, S., Khatun, T., Hasan, M. Z., & Shorif Uddin, M. (2024). *Eye Disease Image Dataset"*. Retrieved from https://data.mendeley.com/datasets/s9bfhswzjb/1