Final Report - Image 6

names

Executive Summary

Short description of the problem. The main findings. Key figure if appropriate. The practical relevance of the analysis.

Aim and Background

A clear description of the problem, articulating the aim of this project. Provides appropriate multidisciplinary context and motivational background explained well in an appropriate language. Including background of the data

Method - Data Collection & Developed Models

Clear description of the approach in data collection, developed model, the evaluation strategies from a data-science perspective. Here we refer to all types of evaluation metrics including graphical, qualitative and quantitative metric.

A clear description of your innovation and approach to the scientific problem.

What is your approach and which tools are used and why?

Baseline Model

Data Augmentation Models

Method - Evaluation Strategies

Results - Effect of Data Augmentation

A clear justification of the final approach based on the proposed evaluation strategies. Ensuring multiple evaluation strategies are used.

Gaussian Noise

Observing Figure 1, the introduction of Gaussian noise in the implementation resulted in an increase in validation loss across all models, as compared to the original model. Notably, the application of random mean Gaussian noise yielded the largest validation loss for both the binary and categorical models. Moreover, a high mean Gaussian noise of 0.8 was applied led to the highest validation loss for both the binary and categorical models with class weights. Finally, the inclusion of low mean Gaussian noise demonstrated the highest validation loss for the RMSprop models, both with and without class weights.
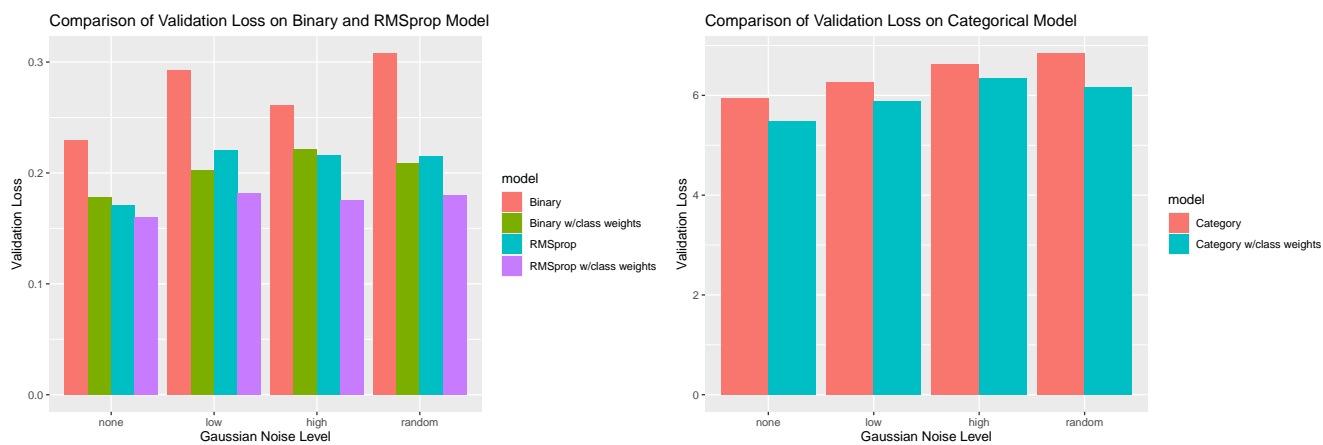
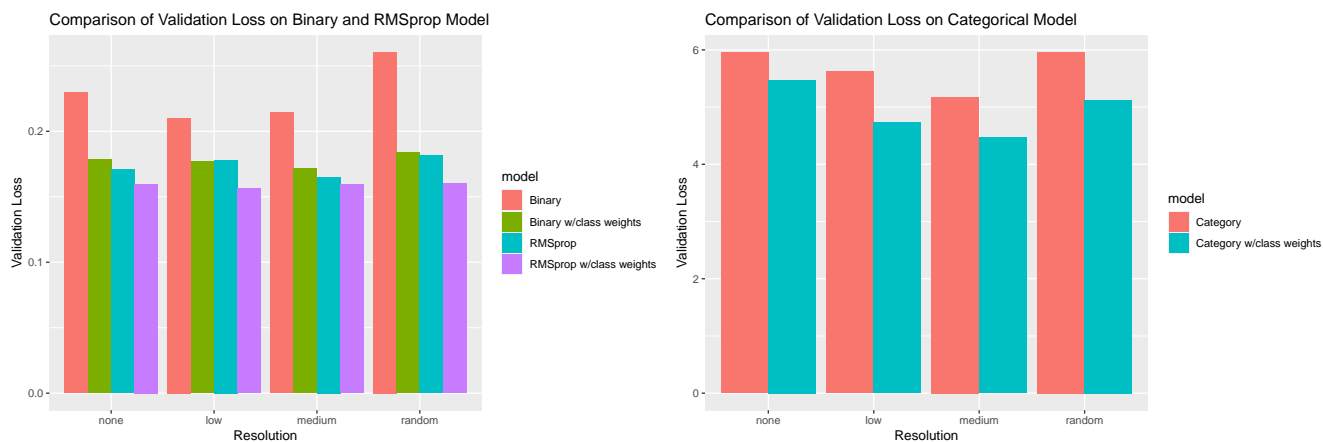Figure 1: Validation Loss for Different Gaussian Noise Levels on CNN Models.

Figure 2: Validation Loss for Different Resolution on CNN Models.

Resolution

The incorporation of low (16x16) and medium (32x32) resolutions in the implementation resulted in a reduction of validation loss across all models, as illustrated in Figure 2. Notably, the categorical models with class weights experienced the most substantial benefits from this augmentation, with a decrease of 0.7503 when low resolution was added and a decrease of 1.0054 when medium resolution was utilized. Conversely, the introduction of random resolution into the training set led to an increase in validation loss, particularly noticeable in the binary model, with an increase of 0.0309.
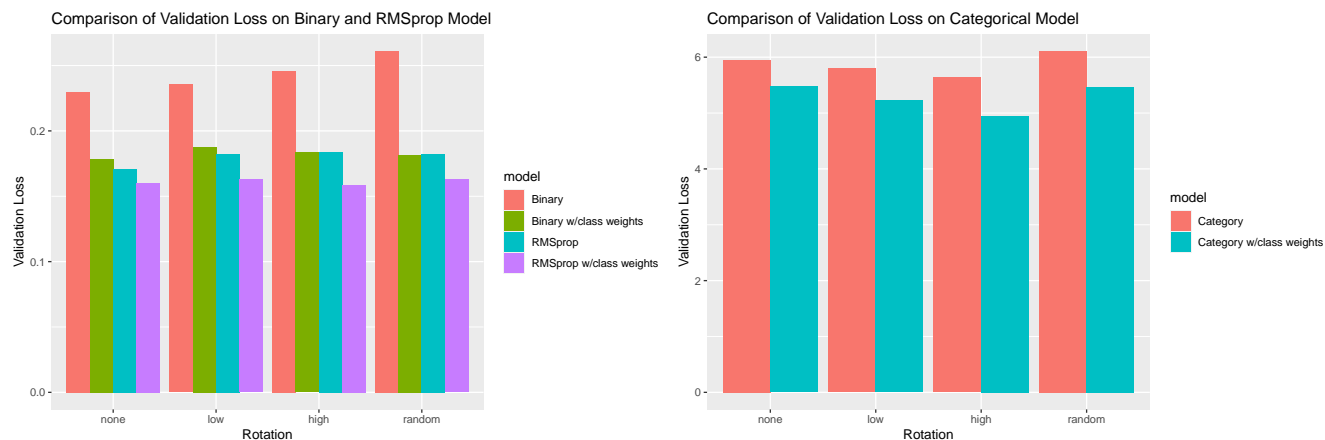
Rotation

Figure 3: Validation Loss for Different Rotation on CNN Models.

From Figure x, it can be seen that...

Results - Deployment

A clear description of the deployment process. An engaging and clear illustration of the product (games, shiny app, learning device etc) with a discussion of concepts from multiple disciplines.

General results notes: Communicate the results to a general scientist, note this is different to the target audience of your product. What are the key findings? and use figures to illustrate the results.

Discussion

How robust and generalizable is your finding or your product?

Discussion of potential shortcomings or issues associated with the development process or the product with reference to both disciplines.

Identification of future work or improvement in both disciplines.

Conclusion

Conclusion adequately summarises the project and identification of future work.

Student Contributions

References

Appendix

Main code & technical details of your approach