Predicting Brain Tumors from MRI Scans Using KNN, CNN, and Pretrained Models

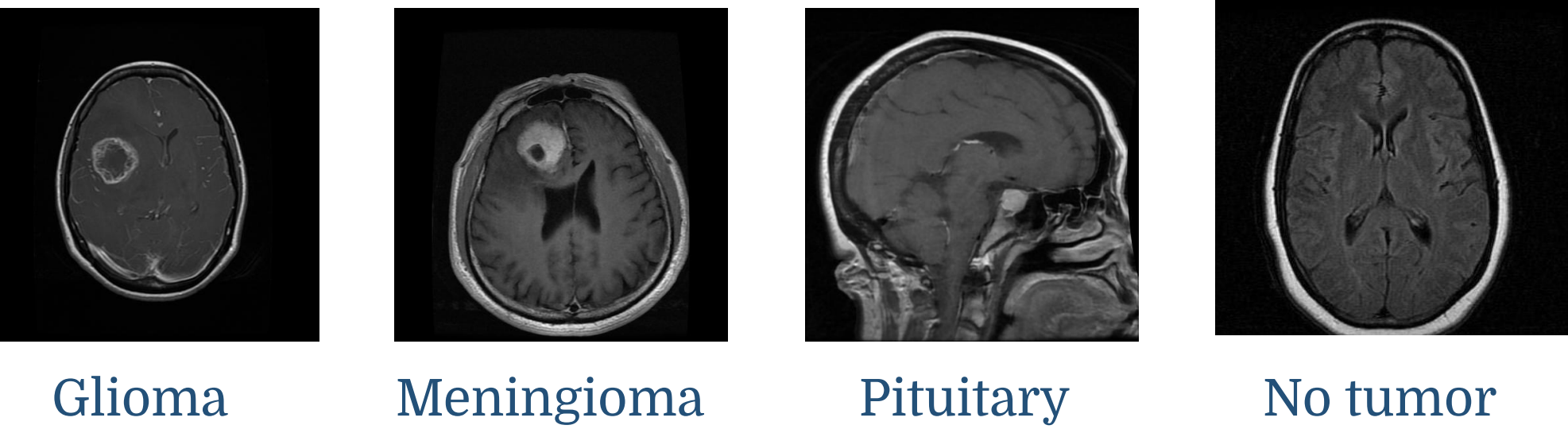Eddie Jang, Amelia Lunning

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Abstract

Brain tumors are destructive, and a misdiagnosis leads to incorrect medical care. An accurate diagnosis is critical for the health and survival of the patient. Research has shown success with computer-aided tumor detection and diagnosis.

We did a study of three models to classify brain tumors from MRI scans. The models used were a multiclass KNN model, a CNN model, and the pretrained CNN model VGG-16.

Our goal was to classify the MRI scans into the following classes: glioma, meningioma, pituitary, and no tumor. We used the Kaggle Brain Tumor MRI Dataset, which had 7023 images.

Here are examples of the classes:

Glioma   Meningioma   Pituitary   No tumor

Introduction

Brain tumors fall into two types: malignant and benign. Malignant tumors are cancerous and grow quickly, while benign tumors are non-cancerous and grow slowly. Some common types of tumors are glioma, meningioma, and pituitary.

Gliomas are tumors that grow within the substance of the brain and are the most common type of brain tumors. High-grade glioma tumors are one of the most aggressive types of brain tumors with a minimal survival of two years (Rehman et al.).

Meningiomas are the most common type of benign tumors, they originate from the membranes surrounding the brain and spinal cord.
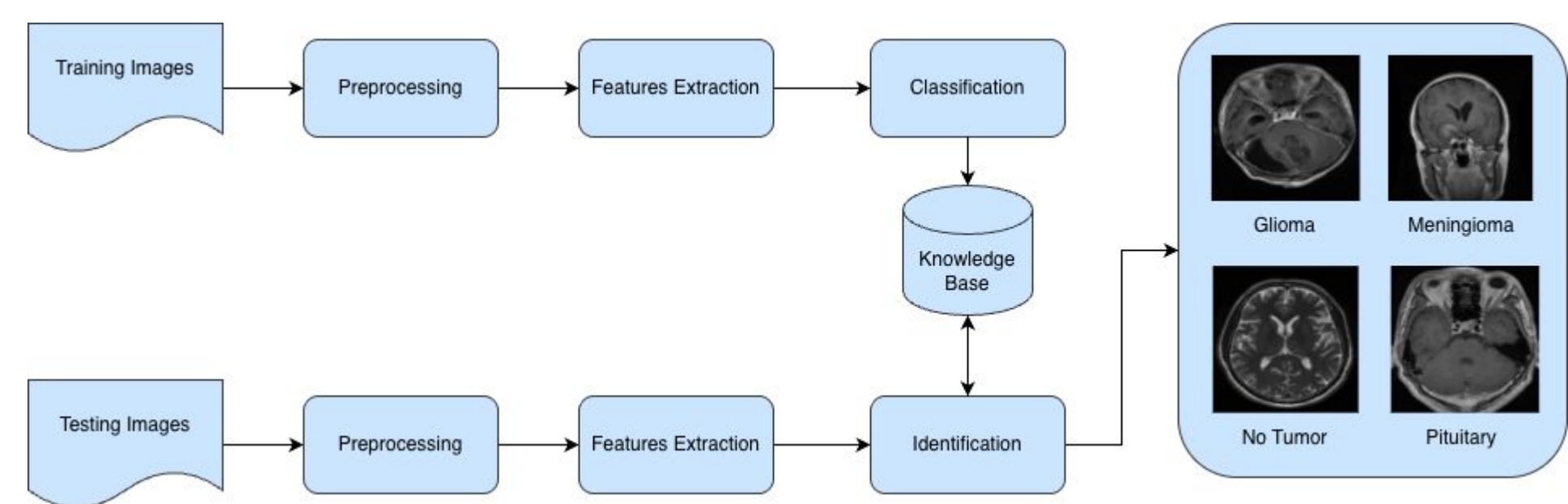
Pituitary tumors are an irregular growth of brain cells that develop in the pituitary gland of the brain, and they're commonly benign.

We wanted to answer the following question: given a human MRI brain scan, what type of tumor does it have?

To answer the question, we used a Brain Tumor MRI Dataset. It contains 7023 images of human brain MRI images which are classified into 4 classes: glioma, meningioma, no tumor, and pituitary. It is already split into testing/training data and it's roughly balanced, with testing containing 1311 images (300 glioma, 306 meningioma, 405 no tumor, 300 pituitary) and training containing 5712 images (1321 glioma, 1339 meningioma, 1595 no tumor, 1457 pituitary).
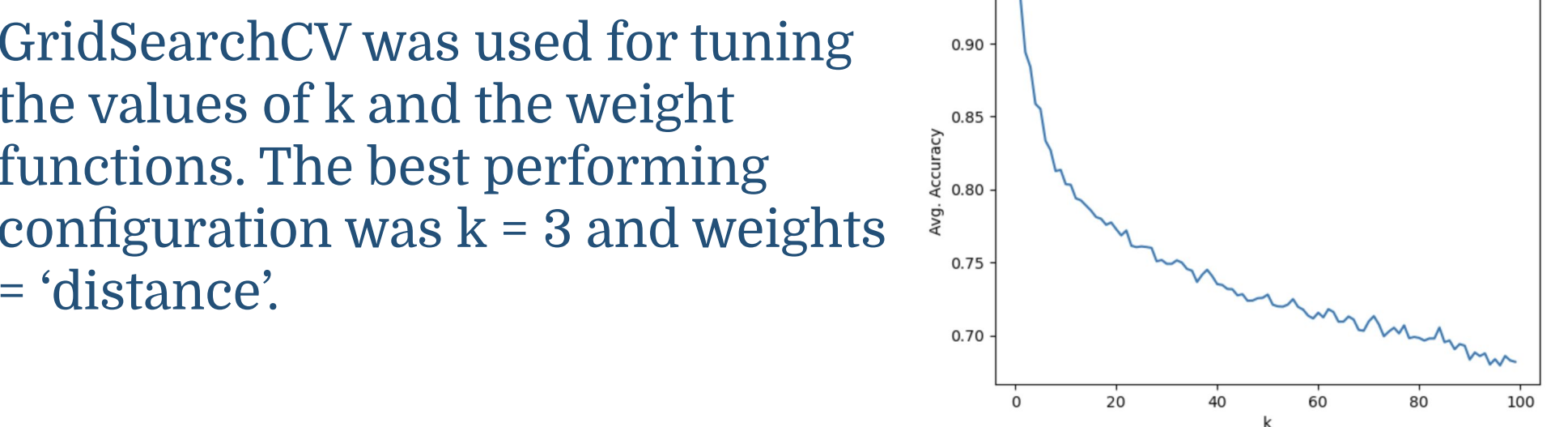
With the dataset, we were able to apply the three models to approach the question: KNN, CNN, and pretrained CNN model (VGG-16).

Methodology

KNN Model

MRI images were dynamically cropped to isolate the brain region and reduce unnecessary background. The image vectors were normalized using StandardScaler, which standardizes each feature to zero mean and unit variance.

GridSearchCV was used for tuning the values of k and the weight functions. The best performing configuration was k = 3 and weights = 'distance'.
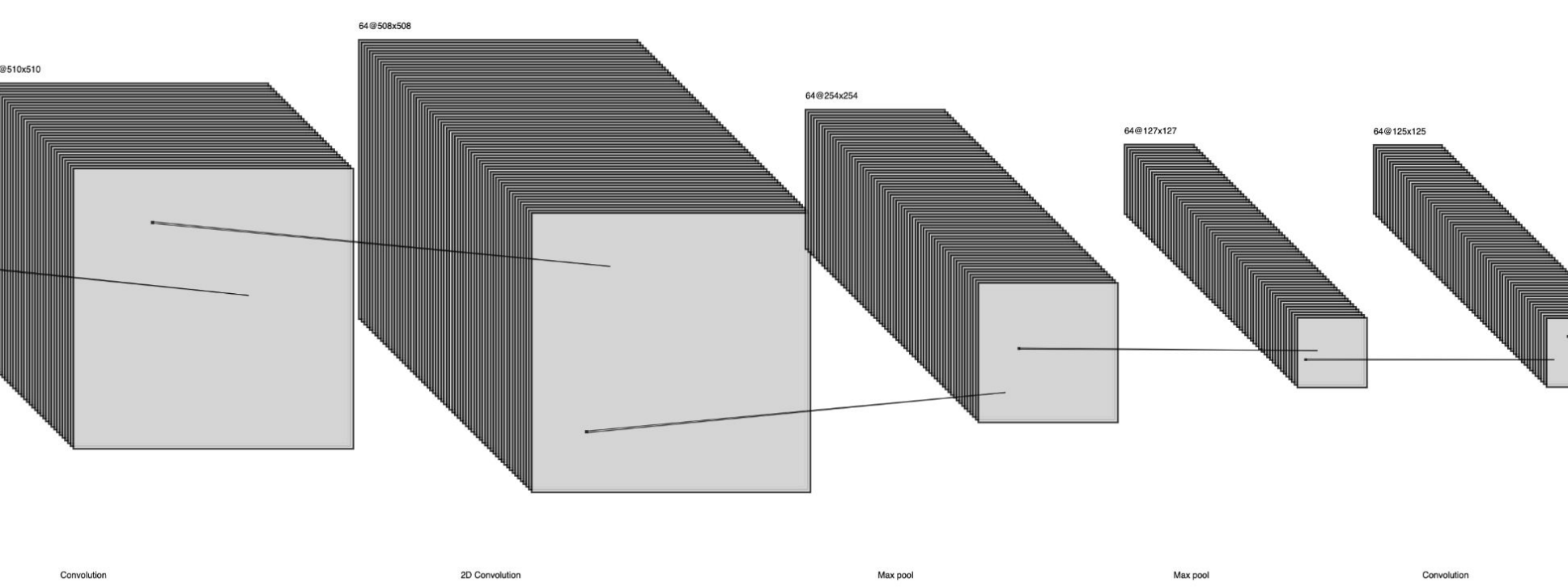

CNN Model

MRI images were horizontally flipped for data augmentation. L2 regularization was implemented by adding weight_decay that is greater than zero on the optimizer. The images were normalized using the standard deviation and mean of RGB value, according to ImageNet. Various methods to prevent overfitting such as normalization, L2 regularization, data augmentation, train-test split, and early stopping.

Using Cross Entropy Loss with Stochastic Gradient Descent at batch size of 8 has improved accuracy of the model.

10 layers for CNN were created using max-pooling, flattening, ReLu, and convolutions.

Pretrained Model

Used VGG-16 with ImageNet weights as a feature extractor.

We chose to use VGG-16 because of previous research done that compared the accuracy of the pretrained models AlexNet, GoogLeNet, and VGG-16. VGG-16 had the highest accuracy of 98.69% (Rehman et al.).
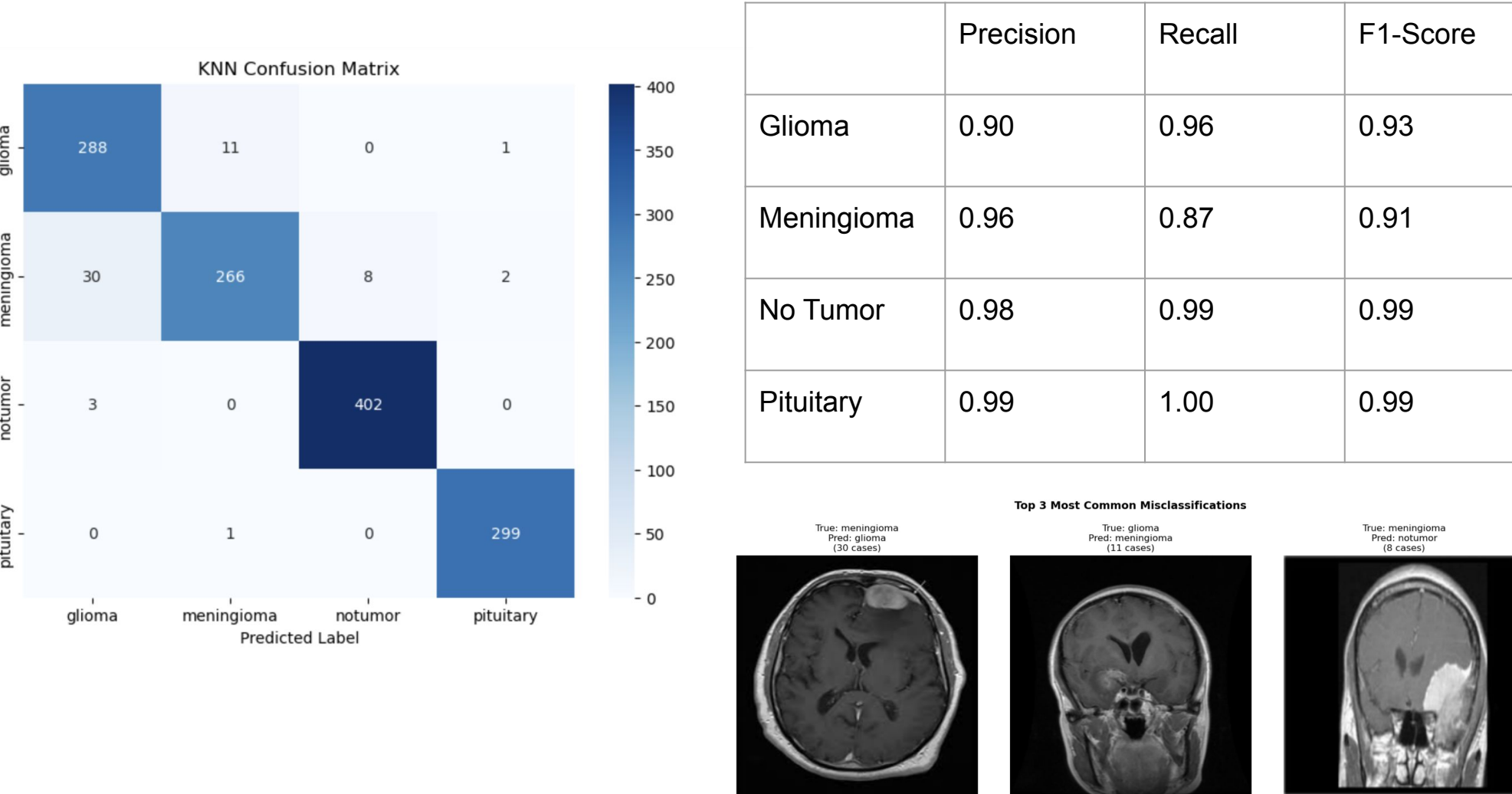
Model was trained for 5 epochs using Adam optimizer and binary cross-entropy loss.
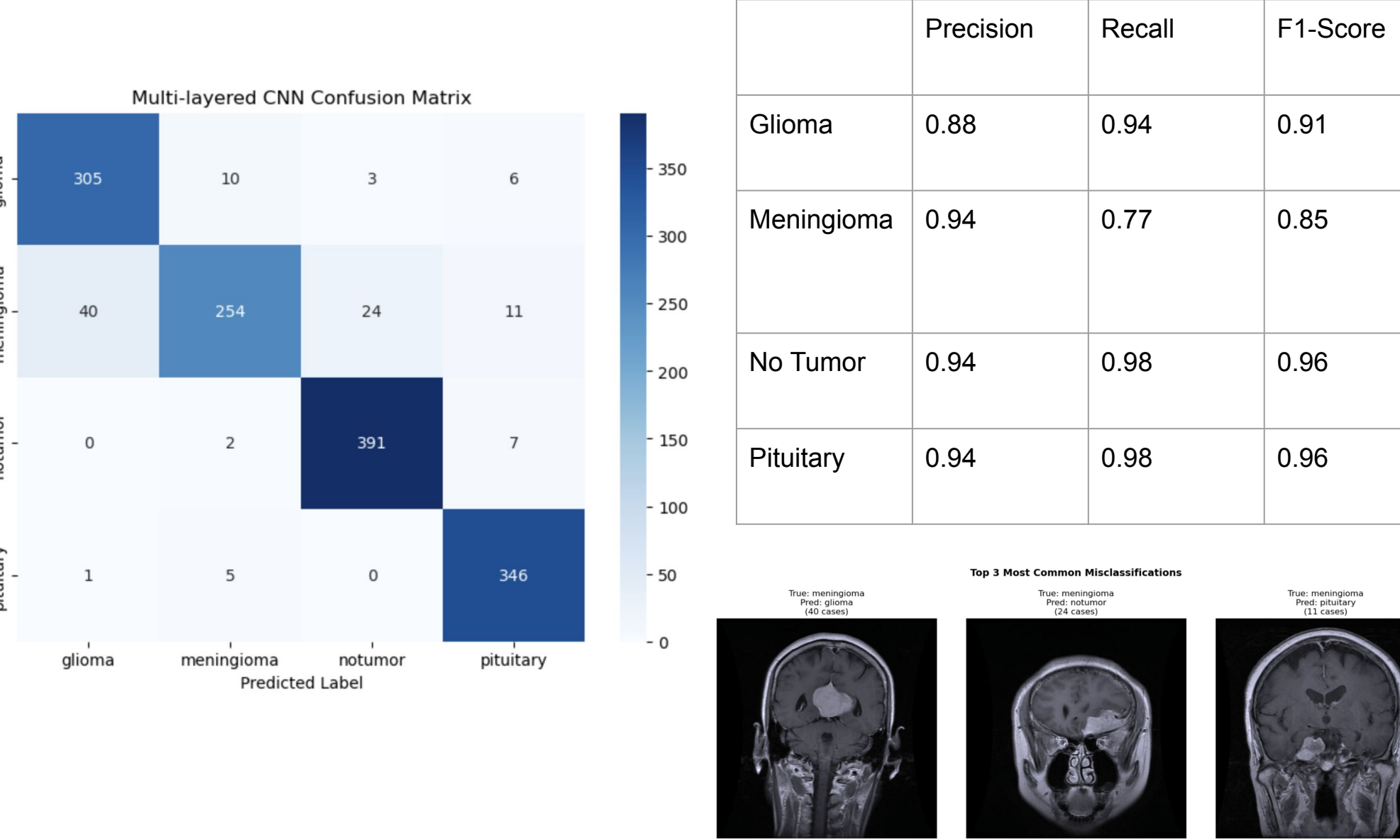
Results

KNN model

The KNN model achieved 96% accuracy.

The most common misclassifications was predicting glioma when it was meningioma (30 cases).

	Precision	Recall	F1-Score
Glioma	0.90	0.96	0.93
Meningioma	0.96	0.87	0.91
No Tumor	0.98	0.99	0.99
Pituitary	0.99	1.00	0.99

CNN Model

The CNN model achieved 95% accuracy.

The most common misclassification was predicting glioma when it was meningioma (40 cases).

	Precision	Recall	F1-Score
Glioma	0.88	0.94	0.91
Meningioma	0.94	0.77	0.85
No Tumor	0.94	0.98	0.96
Pituitary	0.94	0.98	0.96

Pretrained Model

The VGG-16 model has 96% accuracy.

The most common misclassification was predicting meningioma as glioma (24 cases).

	Precision	Recall	F1-Score
Glioma	0.95	0.90	0.93
Meningioma	0.90	0.93	0.92
No Tumor	1.00	1.00	1.00
Pituitary	0.97	0.98	0.98

Conclusion

All three models achieved strong performance, with KNN and VGG-16 scoring the highest accuracies of 96%.

The most frequent misclassification among all the KNN and CNN models was predicting glioma when it was meningioma. The CNN model did this the most, with 40 total cases. VGG-16 did this too.

We realized that having high accuracy does not always mean the best model to use for classification; the context of misclassification is more important, particularly in case of medical conditions.

With glioma being the most aggressive brain tumor among the ones we classified, there is greater importance in correctly identifying these. In this case, recall is the most important because misclassification of glioma tumors can drastically reduce survival rate. The pretrained KNN model has the highest recall for glioma, achieving 96%.

Recommendations

It is recommended avoid using the pretrained model because it misclassifies glioma as meningioma. When dealing with medical data classification, we want to minimize false negative. Although there is no true and positive since the model was multi-class classification model, we could divide the tumors into two types: malignant and benign where malignant tumors could be treated as positives (for being cancerous) and benign tumors could be treated as negatives. Since glioma tumors fall into positive categories, misclassifying glioma as meningiomas could cause a critical outcomes.

Between the KNN model and the CNN model, using the KNN model is recommended because not only it has higher accuracy but also it excels in identifying glioma, the most aggressive type of tumor. In addition, since all precision, recall, and F1-Score values of the KNN model are higher than that of the CNN model, it is recommended to use the KNN model.

Acknowledgements

Rehman, Arshia, et al. "A Deep Learning-Based Framework for Automatic Brain Tumors Classification Using Transfer Learning." Circuits, Systems, and Signal Processing, vol. 39, no. 2, 10 Sept. 2019, pp. 757–775, https://doi.org/10.1007/s00034-019-01246-3.

Msoud Nickparvar. (2021). Brain Tumor MRI Dataset [Data set]. Kaggle. https://doi.org/10.34740/KAGGLE/DSV/2645886