Annapolis Royal

CEC 2025

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Roadmap

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01.

Introduction

The MRI Scan Problem

Theme: ***The Ethical Engineer*** - How does using A.I. (ML) to scan MRI's impact patients?

Problem: The JBOW hospital is experiencing high volumes of patients more than they can keep up with. JBOW Hospital is in need of a program which can interpret MRI scans of the brain, to aid diagnosis and treatment for people undergoing brain injury.

Task: Given an MRI scan in PNG format develop a way to process the image and predict whether or not a given scan contains the marking of a brain tumor with a high level of accuracy and dependency.

Input: A couple thousand training images split up into images with a tumor and images without a tumor.

Output: A csv of image names and whether or not the coordinating image contained a tumor.

Context

On average, 50% of people get an MRI within 64 days. This is still over 2 months. And **can lead to tragedies** like in the case of Destiny Rennie.

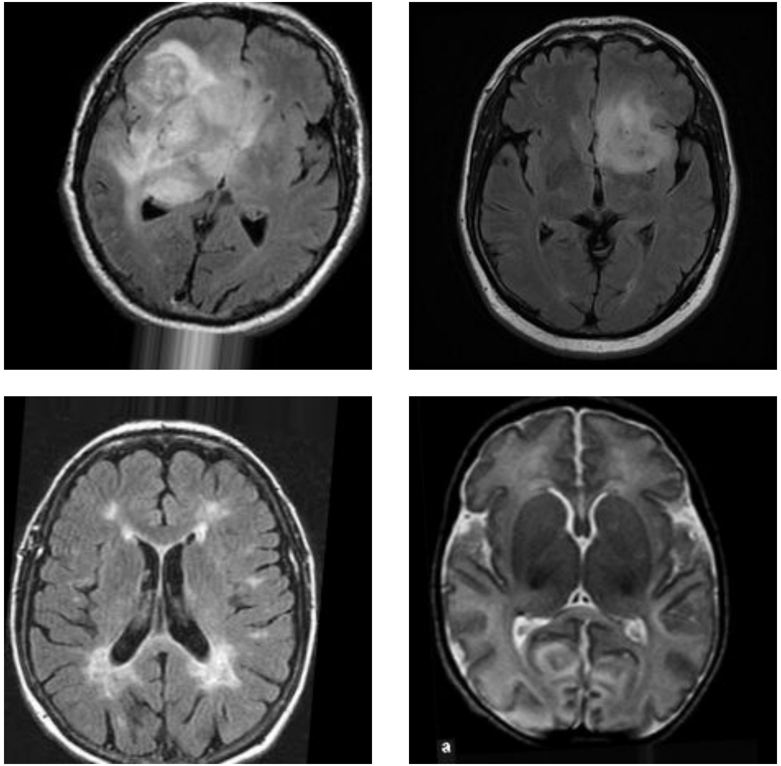
https://waittimes.novascotia.ca/procedure/mri-nova-scotia-health-authority

Why it matters?

There is a lot of strain on the healthcare system not only in Nova Scotia **but all across Canada**. So we need to leverage technology where we can't fill the personnel gaps. Technology can help speed up and simplify medical processes while still maintaining reliability and security of user information.

The average age of a Canadian is increasing; thus **more strain on the medical system will come in the coming decades.**

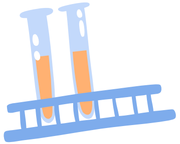
https://www.statista.com/statistics/444844/canada-median-age-of-resident-population/



Data Overview

Input Data: Was scrubbed MRI's meaning no personal data or identifying markers were present to identify the individuals. Relatively hard tasks as tumors don't have a defined shape. We also utilized data transformation for model training.

Output Data: A CSV file with image file name and a yes/no based solution prediction, an output based on a image inputted by a user.



02. Methodology/ Considerations

Design Considerations

Simple to use

Program is intended to be used by doctors and medical technicians so there should be a relatively small learning curve and a simple intuitive UI

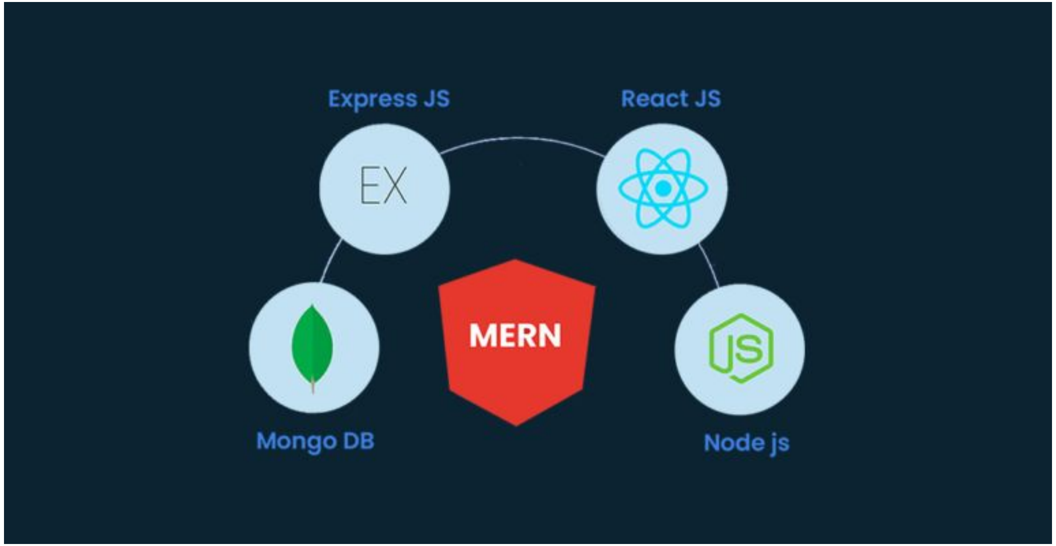
Practical

A widely available tech stack and implementation would allow for better future modifications and easy debugging.

Efficient

An efficient solution was chosen as time is our biggest constraint; speeds up training.

Tech Stack



https://www.jaroeducation.com/blog/what-is-mern-development-how-to-use-mern-stack/
https://en.wikipedia.org/wiki/Python_%28programming_language%29
https://rock-the-prototype.com/en/software-development/github/

03.

Our Algorithm

Our Model

We used EfficientNetV2 with ImageNet1K. (convolutional neural network)

- As a Criterion we used **Cross Entropy**. (classification)
- As an Optimizer we used **Adam**.
- As a Scaler we used **Grad Scaler**.
- We decided to start with **5 Epochs**.

Why these models?

EfficientNetV2 offers a strong **balance of accuracy and efficiency**, outperforming models like ResNet and Inception. It works well across tasks **such as classification,** segmentation, and detection, since it is **optimized for these tasks.**

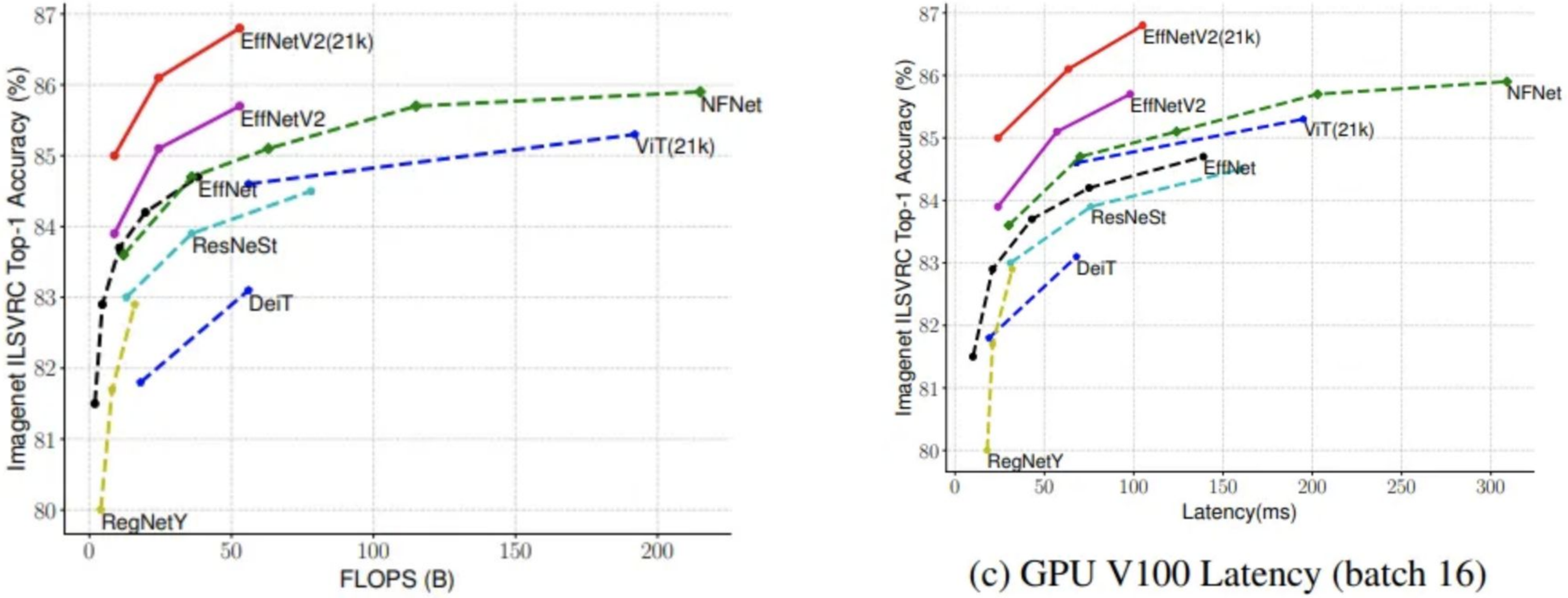
We chose it over ResNet and VGG due to its superior efficiency and scalability. With just 5 epochs and data augmentation, **it converges faster,** and using ImageNet1K pre-trained weights speeds up training further.

Adam optimizer and GradScaler enhance convergence and efficiency by adjusting the learning rate and reducing memory usage, making training faster and more efficient compared to ResNet and VGG, which require more data and epochs.

Due to the time constraint ability to train and verify our models was front and centre.

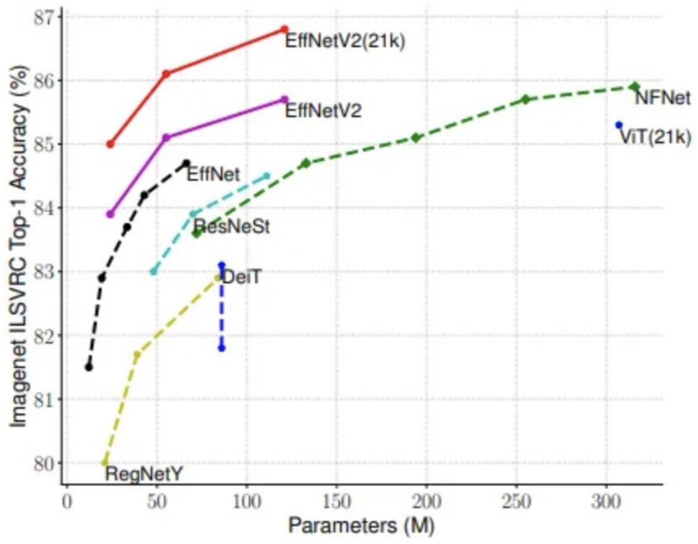
https://medium.com/data-science/efficientnetv2-faster-smaller-and-higher-accuracy-than-vision-transformers-98e23587bf04

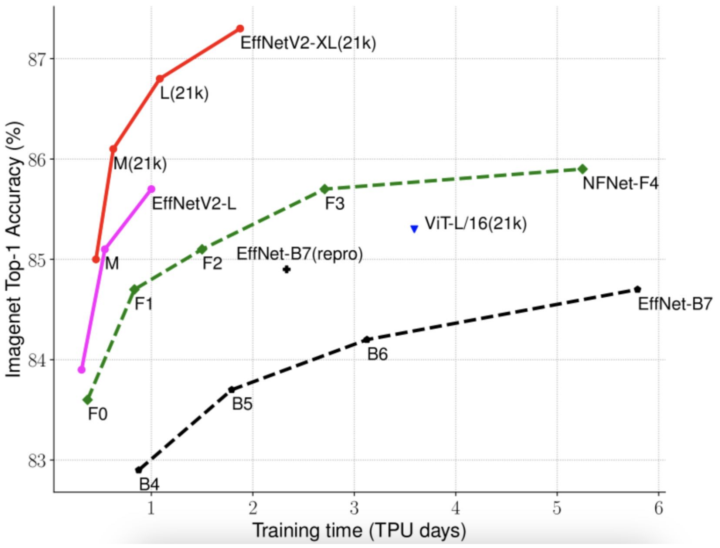
Why these models?



https://medium.com/data-science/efficientnetv2-faster-smaller-and-higher-accuracy-than-vision-transformers-98e23587bf04

Why these models?





https://medium.com/data-science/efficientnetv2-faster-smaller-and-higher-accuracy-than-vision-transformers-98e23587bf04

How the model works?

How the model operates: The Convolutional Neural Network (CNN) layers in the model are designed to automatically detect various patterns, edges, and shapes within the input images. As the image data passes through these layers, the model learns determines based on its training, whether or not a tumor is present, returning either a true or false result based on the learned patterns.

How the model was trained: The model was trained using a wide range of data transformations, such as rotating, flipping, and adjusting the hue and saturation of the images. The transformed images were then converted into tensors, which are the data format required by the model. During training, the model's parameters were fine-tuned through multiple iterations.

04.

Solution

Features/Solution

01.

CSV output

Our solution outputs the result, confidence level and likelihood of correct result for transparent results.

02.

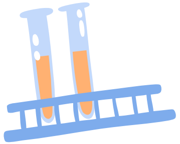
User Interface

We utilized a simple UI for medical practitioners to interface with the model. We also display all relevant info for accurate interpretation.

03.

Pre-trained Model

The pretrained model gives this solution a high level of reliability and accuracy.

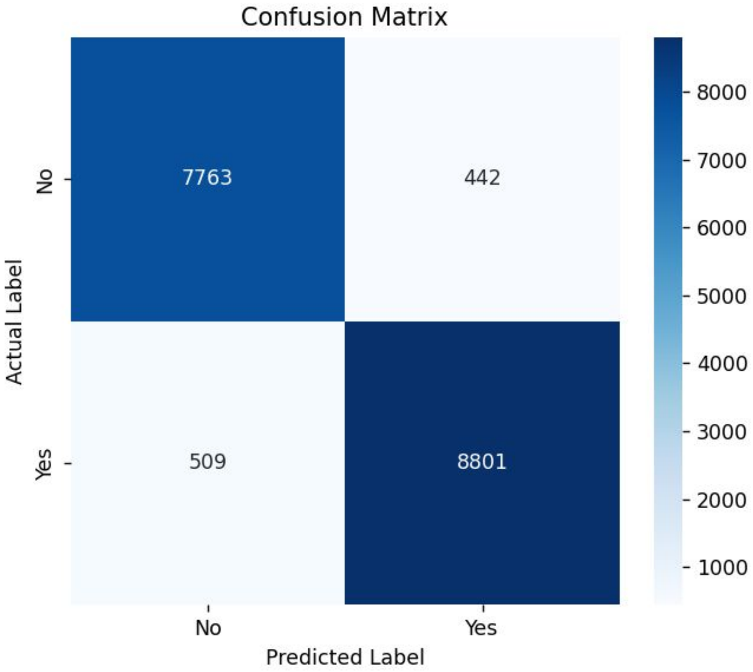


05. Demo and Code Review

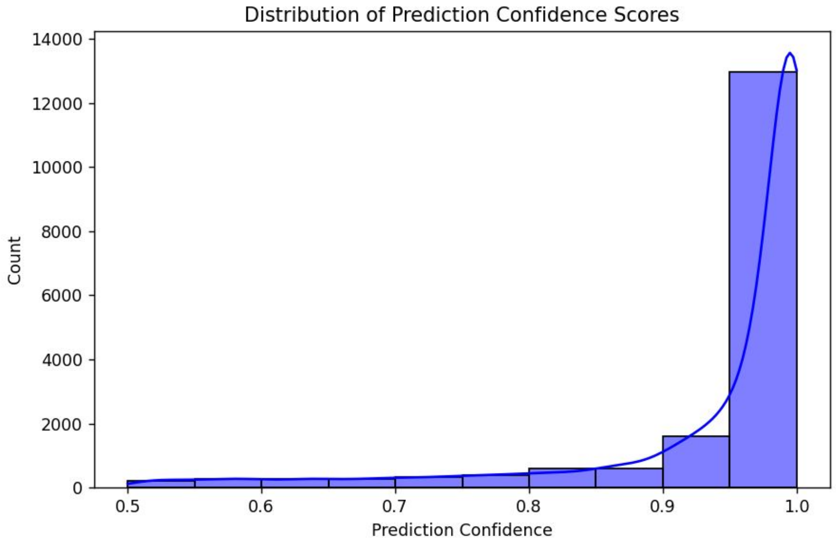
06.

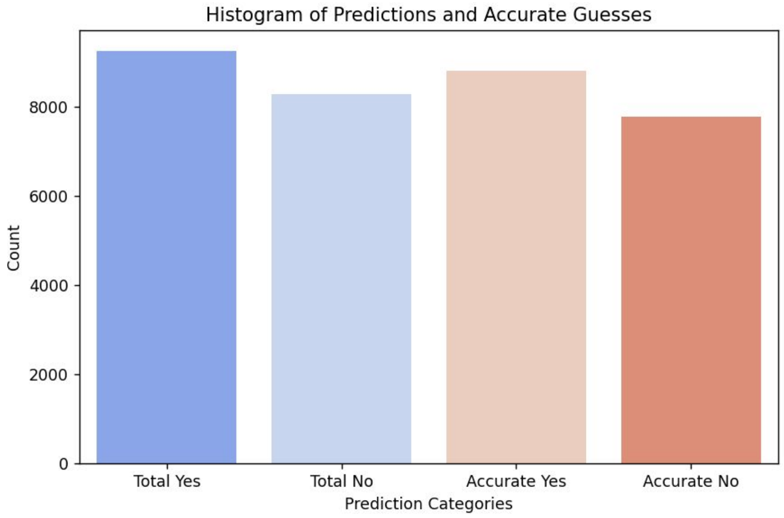
Dataset/Results

Confusion Matrix



From this we can calculate a 94.7% data accuracy


Distribution of Prediction Confidence Scores
14000
12000
10000
8000
6000
4000
2000
0
Count
0.5
0.6
0.7
0.8
0.9
1.0
Prediction Confidence


Histogram of Predictions and Accurate Guesses
8000
6000
4000
2000
0
Count
Total Yes
Total No
Accurate Yes
Accurate No
Prediction Categories

Dataset Results

KEY:
First Letter: S (Small, more efficient model), M (Medium, bigger, less efficient model, supposedly more accurate)
Second Letter: S (Simple transforms), A (Advanced transforms like changing hue and saturation)

v2_s - simple transforms - SS
Trained off 100 random images:
- Testing with 100 random images: 92.00%
- Testing with 1000 random images: 87.10%
- Testing with 5000 random images: 88.68%

v2_s - simple transforms - SS
Trained off 250 random images:
- Testing with 100 random images: 93.00%
- Testing with 1000 random images: 92.50%
- Testing with 5000 random images: 92.28%

v2_s - simple transforms - SS
Trained off 500 random image:
- Testing with 100 random images: 93.00%
- Testing with 1000 random images: 95.00%
- Testing with 5000 random images: 94.42%
- Testing with 10000 random images: 94.53%
    - 2nd: 94.62%

v2_s - simple transforms - SS
Trained off at 750 random images:
- Testing with 100 random images: 93.00%
- Testing with 1000 random images: 93.30%
- Testing with 5000 random images: 92.92%

v2_s - simple transforms - SS
Trained off 1000 random images:
- Testing with 100 random images: 98.00%
- Testing with 1000 random images: 94.40%
- Testing with 5000 random images: 93.72%
- Testing with 10000 random images: 93.93%
    - 2nd: 93.55%

v2_m - simple transforms - MS
Trained off 100 random image (Advanced):
Testing with 100 random images: 81.00%
Testing with 1000 random images: 83.80%
Testing with 5000 random images: 82.40%

v2_m - advanced transforms - MA
Trained off 100 random image (Advanced):
- Testing with 100 random images: 85.00%
- Testing with 1000 random images: 88.10%
- Testing with 5000 random images: 87.20%

v2_m - advanced transforms - MA
Trained off 500 random image (Advanced):
- Testing with 100 random images: 82.00%
- Testing with 1000 random images: 89.90%
- Testing with 5000 random images: 87.40%

07.

Troubleshooting

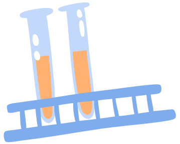
Issues Faced

Selecting the Model

Initially we didn't know which model to use, but we ended up with EfficientNetV2, after each group member ran test models.

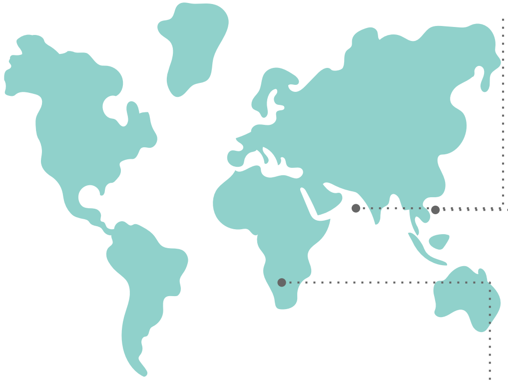
Accuracy Issues

At the start of testing, we had a roughly 70-80% accuracy which was not ideal. But as we continued to train, we ended up at ~94%.



08. Future Implementations

Technical Implementations



Higher Accuracy

Given the time constraint we were limited to what we had, but given more time, we would be able to increase the accuracy more.

Custom Model Implementation

Given more time, we believe a more custom solution may be more beneficial as opposed to a pre configured model due to nature of images. Use of a more efficient language like C#.

Allowing for more file types

Actual MRI file types such as DICOM (.dcm) and NIfTI (.nii, .nii.gz).

Ethical Considerations

Sensitive Data

MRI scans and the medical info they contain about a person is highly personal and therefore protected information. The AI model must run in a contained environment (local) and prevent the release of information into bad actors hands.

Data Bias

AI can only predict as good as the data set that it was trained on. We need to make sure that the data set includes people from all walks of life. For example if this data set is mostly adults what would be the repercussions if used on a child's scan?

Patient Consent

Even if the Program is 100% secure the patient should still have the right to accept AI use or not as they have rights over how their medical info is used and processed especially when it comes to new technology.

09.

Conclusion

Conclusion

Accuracy

Our Model is 94.77% accurate offering reliable results.

Simplicity

The Program is built on pretrained models customized to our use and is a lightweight solution.

Efficiency

Our test set can process 1000 images in under 2 minutes on a regular machine.

UI

The simple and easy to use UI makes this an appealing application.

THANKS!

Do you have any questions?

CREDITS: This presentation template was created by Slidesgo, including icons by Flaticon, and infographics & images by Freepik and illustrations

References

ChatGPT: for library referencing of calls/functions/features, errors/helping debug issues, algorithm development.

https://github.com/Sha3-git/CEC25

https://medium.com/data-science/efficientnetv2-faster-smaller-and-higher-accuracy-than-vision-transformers-98e23587bf04

https://paperswithcode.com/method/efficientnetv2#:~:text=EfficientNetV2%20is%20a%20type%20convolutional,to%20jointly%20optimize%20training%20speed.

https://arxiv.org/pdf/2104.00298#:~:text=Our%20ex%2D%20periments%20show%20that,causes%20a%20drop%20in%20accuracy.