AI for Alzheimer's

Swetha Bhumireddy, *Member, Artemis*, Christian A. Chapman, *Member, Artemis*, Bryan D. Richlinski, *Member, Artemis*, James H. Ta, *Member, Artemis*

***Abstract* — A deep learning model was built to classify patient brain scans with Alzheimer's or No Alzheimer's to assist medical professionals. This model was trained with MRI scans from two different sources and was able to achieve results above 90 percent. This article goes over the details behind our process which included decision making, model construction, model training, final application, and solutions.**

***Index Terms* — Introduction · Problem Statement · Application · Related Work · Solutions Explored · Datasets · Preprocessing · Model · Postprocessing · Conclusion · References**

NOMENCLATURE

· Alzheimer's: Type of brain disorder that progressively causes deterioration in the brain, causing loss of memory, mental functions, and basic motor functions; it is also the most common cause of dementia [1].

· MRI: Magnetic Resonance Imaging. Form of non-invasive medical imaging that allows for the creation of detailed three-dimensional anatomical images using magnetic fields and computer-generated radio waves [1].

· NIfTI: Type of file format for neuroimaging developed by the NIH's Neuroimaging Informatics Technology Initiative that is capable of preserving the spatial information of a brain scan [1].

I. INTRODUCTION

THIS project looks into the possibility of implementing deep learning algorithms in order to better assist in the diagnostic criteria involved in providing an assessment on whether or not a patient has Alzheimer's Disease based on their MRI scan. This project shows a possibility of being expanded into other use cases in the medical field, such as for concussion detection or brain tumor detection, however, we specifically chose to focus on Alzheimer's for the purposes of this project. Alzheimer's Disease is a brain disorder that causes dementia. One of the hallmarks of this disease is a development of amyloid plaques in the brain as well as a significant decrease in brain volume. Alzheimer's Disease causes neurodegeneration that results in a significant change in structure of a patient's brain. Our work focuses on creating a deep learning model that is capable of detecting these changes and analyzing them to determine if they are indicative of a patient possibly having the disease. Our model works by taking in a patient's MRI scan and analyzes the structural information provided in the scan before outputting a diagnostic evaluation based on the data that had been collected.

II. PROBLEM STATEMENT

We are attempting to build a model that would be capable of detecting Alzheimer's based on a patient's provided MRI scan. The program would allow for a healthcare provider to upload a NIfTI file of a patient's brain scan and after running through the model, the program would provide an output of the likelihood said patient has Alzheimer's. The model will classify the brain scans as either Alzheimer's or No Alzheimer's diagnoses. This would assist in expediting the evaluation and diagnostic process when evaluating patients for Alzheimer's while having radiologists extensively check through a scan. It would also provide a secondary, unbiased, assessment based on certain diagnostic criteria to assist the medical professional better make a differential diagnosis on their patients.

III. APPLICATION

We made a web application to allow medical personnel to upload NIFTI files of brain scans and get the results of the model prediction: Alzheimer's/No Alzheimer's. We constructed the full application using ReactJS, Flask, and Keras. ReactJS was used to develop our frontend, Flask was used to host our web server and to allow our frontend to connect with our backend Keras model, and Keras was used to develop our Deep Learning model. In a production environment, this application would be distributed to hospitals for use by healthcare professionals. This would allow for healthcare providers to have an additional diagnostic metric when assessing patients for Alzheimer's. Our application would be a faster, cheaper, and more accessible clinical tool for doctors when diagnosing patients with Alzheimer's.

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S. Bhumireddy is with the University of Missouri Kansas City, Kansas City, MO 64110 USA (e-mail: sbcfw@umsystem.edu).

C. A. Chapman is with the University of Missouri Kansas City, Kansas City, MO 64110 USA (e-mail: cac8fc@umsystem.edu).

B. D. Richlinski is with the University of Missouri Kansas City, Kansas City, MO 64110 USA (e-mail: bdrxbc@umsystem.edu).

J. H. Ta is with the University of Missouri Kansas City, Kansas City, MO 64110 USA (e-mail: jhtwhb@umsystem.edu).

IV. Related Work

Currently, medical brain imaging is capable of detect biomarkers such as amyloid and plaque buildup in the brain. However, symptoms of Alzheimer's predominantly show up long after early indicators of these biomarkers are present in the brain. Consequently, it is in the medical community's best interests to be able to analyze and detect these biomarkers through brain scans early on so as to diagnose and start treatment on patients well before symptoms start presenting which would indicate later stages and progression of the disease. Our project intends to use a CNN classifier to detect plaque and amyloid buildup prior to a patient becoming symptomatic. This would allow for non-invasive early Alzheimer's detection. Other projects attempt to detect Alzheimer's by doing things such as monitoring eye movements as there is a change in latent eye movement caused by the neurodegeneration brought on by the disease. The Kaggle dataset mentioned earlier uses jpeg images instead of NIfTI files of the MRI brain scans in order to process the files and determine an indication of Alzheimer's. Some other studies have been done using PET scans instead of MRI scans in order to check for indicators of Alzheimer's. These studies are focused more on capturing the presence of amyloid plaque build up in the brain as opposed to MRIs being used to check for structural changes and deterioration in the brain.

V. Solutions Explored

Throughout the duration of this project, multiple solutions have been explored. They have involved multiple different datasets, as mentioned in the following Datasets section. The solutions/models that were based off of the first two datasets didn't provide the results we were hoping for. As we were running out of time, we decided to try a new solution that involved a new dataset in hopes that we would be able to train a model with good accuracy. We found a dataset from Kaggle which allowed us to train an accurate model. Although, we didn't stop here with this model, as we still wanted to use our second dataset as input data to a model (the Kaggle dataset was only JPG images, whereas the second dataset was actual NIfTI files). So transfer learning techniques were brought in to develop a new model based off of the Kaggle dataset model to train on the NIfTI files, and this allowed us to get good accuracies while also using the NIfTI files. We also explored a couple of different solutions with regards to how to use our model and connect it to our frontend. Initially, the plan was to do everything in JavaScript in the production environment (except for model development) since that was where our codebase for the front end was. So we transferred our model from Keras to TensorflowJS, but ran into issues with trying to apply preprocessing to the uploaded files. This made us move over to Flask, which gave us the opportunity to use NumPy to complete preprocessing steps before passing the data into the model.

VI. Dataset

We used three different datasets over the course of this project. These were the OASIS (Open Access Series of Imaging Studies) dataset [3], ADNI (Alzheimer's Disease Neuroimaging Initiative) dataset [2], and the Kaggle Alzheimer's Disease Classification Preprocessed dataset [7]. After extensive exploration of these datasets, we ended up no longer using the ADNI dataset. We built our original model using the Kaggle dataset, which helped us create a model that was familiar with the types of imaging that would be used in the current dataset and retained a very high accuracy rate. Since the dataset was normalized for the most part, we did not need to spend much time preprocessing, but spent most of our time adjusting the model to our needs. We then applied a similar, but more complicated preprocessing step to the OASIS dataset, which then allowed us to create a novel dataset. Because of this, we were able to quickly train a new model, using transfer learning, that was applicable on a broader file format.

VII. Preprocessing

Our preprocessing algorithm consisted of multiple steps in order to prepare our data for our model. We receive a NIfTI file and end up pulling out specific gray scale images from the NIfTI scans. The first thing we did was to normalize the depth of our NIfTI object to 256 slices (each slice is a different image at a different level of the brain). The algorithm then grabs the slices which provide the most detail on the ventricles (approximately 20 slices, the ones from slice 140 through 160). Following this, the scans needed to be cropped up to the edge of the brain. This was done by finding the first light intensity value in row order of the list that was greater than the average light intensity of the list. After finding this value, all rows of pixels before this are removed and are replaced with a padding of 25 pixels to this side of the image. Then the image is rotated and the process for cropping and padding is replaced for the next three sides as well. Following this, the size of the images are reshaped to an acceptable size of 128x128 and is also converted to a NumPy array. A NumPy array is necessary to allow it to be passed into the model.

VIII. Model

Our final model was built in Keras and it involved transfer learning from the initial model on our Kaggle dataset to a similar model that was then trained with NIfTI files. We were able to use transfer learning to a new model due to the similarity of our datasets between the two different models along with the NIfTI dataset being too small to train a model on its own (the Kaggle dataset was much larger). We built the model with a very simple convolutional architecture. The architecture consisted of an input that expects an image of size 128 x 128 x 1, 3 blocks of convolutional layers that consisted of a Conv2D layer plus a max pooling layer, a layer for flattening, a dense layer of 128 neurons, and an output layer of

one neuron. We took the NIfTI file, which goes through a tedious normalization preprocessing algorithm and results in an array of about 20 meaningful slices. The slices are then sent through the model, which then returns a list of probabilities. The model resulted with a testing accuracy of 99.96% with a 10% testing data split. When training with transfer learning on the model, we froze the convolutional layers and were only training on the dense layer. This allowed for a very fast training effort since most of the layers were frozen. During training, we noticed that from the very first epoch we had high accuracy and very low loss. This trend continued throughout the training of the model as we quickly approached our plateau of 99% testing accuracy.

IX. Postprocessing

Our post-processing algorithm is pretty straight forward, as there is not a ton of work needed to do to interpret the results. After gathering the results of all 20 images from the patient's scan, the scores of each image are all averaged together to give one conclusive answer (if greater than 0.5, the patient is diagnosed, if less than 0.5, the patient is not diagnosed). This answer is sent to the front end to be displayed to the user.

X. Conclusion

Overall, our process included gathering various datasets and determining the one that allowed us to create a model that fit our needs. From there, we took it a step further and took that same model and applied transfer learning. Transfer learning allowed our model to take the data learned from a similar dataset and apply it to our novel dataset. The results from applying transfer learning turned out very well and resulted in a very high accuracy rate. We would like to take away from this project that it is indeed possible that Alzheimer's can be detected using patient NIfTI file scans. We were unsure how possible this was at the beginning, and this was reinforced until we implemented our transfer learning solution. In addition to this, it's important to recognize how beneficial transfer learning can be to an algorithm. It allowed us to be able to take an existing model on one dataset and apply it to a much smaller dataset whose data was much more valuable to our users. This process we created can now allow medical professionals to potentially identify individuals with Alzheimer's and for this process to become more automated.

XI. References

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