Can Machine Learning be effective in the prediction of an autism disorder?

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2 Abstract

In this report, the efficiency of Machine Learning when predicting an Autism diagnosis is evaluated. Three image classification models were trained and tested using a dataset with children's facial images, all achieving an accuracy of testing above 80%, where one of the models achieved 92%. People with an Autism disorder suffer from impairments in social and communication skills, and its often diagnosed late due lack of effective diagnosis methods. Machine Learning algorithms have been being applied in the medical field. Due its ability to learn patterns and replicate them, Machine Learning can be very effective when predicting a medical diagnosis, based on images or sounds, for example. Patients with Autism develop different facial features, which allows research to be applied on images in order to reach a diagnosis. So, Machine Learning can be used to predict an Autism diagnosis, by analysing images of patients. From the classification models created, one was trained on the dataset from scratch, where two of them were created using two pre-trained models: MobileNetV2 and ResNet50. The models are trained and tested using 2,938 images of children, where some are labelled as "autistic" and others "non_autistic". From the three, the model created from scratch achieved the highest testing accuracy of 92%. Whereas the pre-trained models achieved lower. Based on these results, it was concluded that Machine Learning can be effective at predicting an Autism diagnosis. The models created can be adapted for other disorders that allow diagnosis based on images.

3 Acknowledgments

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4 Introduction

Machine Learning (ML) has been reshaping technology in the present world. Computers no longer have to be taught how to perform tasks like image recognition, or sound analysis, since now, there are systems that allowed them to learn for themselves. As a subpart of Artificial Intelligence, ML algorithms are able to look for patterns in data, and predict outcomes based on those patterns. ML is now present in almost every sector of humans' daily lives like finance, transportation, advertising and even healthcare.

In healthcare, people with the same disorders/diseases normally present the same symptoms and patterns, these being recorded. For example, if X-Rays that were taken from people with lung cancer were individually analysed, there would be similarities. Referring to ML in healthcare, Machines can learn these patterns by scanning the images and can predict this diagnosis in other images. Thus, ML can possibly be beneficial for prediction of a medical diagnosis.

Autism is considered as a neurodevelopmental condition, characterized by impairments in social interaction and communication. Presently, diagnosing Autism in individuals has no specific method. Due its complex heterogeneity, diagnosing and even addressing some of the symptoms, is a complicated process (Huerta, 2013). Although, there are methods of diagnosing Autism in individuals, they show poor efficiency. Besides, that, since Autism presents impairments in social interaction, it's important that its diagnosis is made early and screening methods often can be biased. Thus, Machine Learning can be useful on predicting this diagnosis and further help children live a better life.

This report aims to study Machine Learning's effectiveness on prediction of an autism diagnosis. While there has been previous research on Machine Learning prediction algorithms on ASD, none has focused on comparing different methods and models to test this theory. It's noteworthy to point out how important it is to early diagnose correctly an Autism disorder. Due to its impairments, if not treated from early, Autism can disrupt people's lives. So, investing in ML for prediction methods, can improve diagnosis method and allow people with Autism to receive early treatment, which would, consequently, allow them to live a better life.

In Machine Learning, image classification algorithms can be created and tested to predict a diagnosis, based on facial features. However, there are a lot of problems with data and methodology, so different approaches should be investigated in order to reach a correct diagnosis. Data can be clinically incorrect, which would lead to a possible creation of invalid classification models, so that should be something to be careful with.

To prove the theory in question, creation and comparison of different classification models is going to be done, using transfer learning in two of them, and evaluate their performance. The models are going to be trained using a dataset containing children's facial images and tested on different images, to see accuracy of prediction. In the literature review chapter, a deep dive into Autism is taken, addressing its prevalence and problems with late diagnosis. The author also refers to Machine Learning studies into the medical field and refers to several studies addressing its benefits. In the Methodology chapter, the author presents the models to be created and tested. The author is going to create three models, where two of them were developed using transfer learning i.e. models that were pre-trained with large datasets and acquired useful features that can be used in the present dataset. The author pretends to evaluate its performance based on accuracy of prediction. In the Results chapter, the author is going to present this evaluation, with the results of the experience. Later, in the Discussion, the author means to discuss the results and its implications for the world, as long with the limitations for the study.

5 Literature Review

5.1 Autism

5.1.1 *Definition*

Autism has been defined by the American Psychiatric Association (APA) and the 5th edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) as a neurodevelopmental condition, characterized by impairments in reciprocal social interaction, speech and non-verbal communication and restricted and repetitive behaviours (2013). The condition is part of a spectrum denominated Autism Spectrum Disorder (ASD) where, according to the DSM-5 the diagnostical criteria for the spectrum includes multiple diagnosis: autistic disorder, Asperger's disorder, childhood disintegrative disorder and pervasive developmental disorder. Whilst there's multiple conditions in the spectrum, specific characteristics prevail across ASD-positive individuals: failure in controlling or understanding emotions, avoidance of eye contact and a restricted range of activities and interests (APA, 2013). Inherently, these conditions affect daily lives of individuals suffering from the condition.

5.1.2 *Prevalence of Autism*

According to the British Medical Association (BMA), its estimated that around 700,000 people in the UK have autism, where 1 in 100 children have an autism diagnosis. The population suffering from ASD has been increasing in the past decade. Since 1978, where 1 in 10000 people were diagnosed as autistic, this disorder now affects 1% of the global population (Baron-Cohen, et al. 2009). Prevalence of autism has always been the same, however, this increase is noticeable due to diagnosis method improvement, as we will see in the next chapter. Changes such as in how studies were being performed, as also in an increase of diagnostic services and awareness within parents and professionals, led to a substantial increase in diagnosed individuals.

5.1.3 *Problems with late diagnosis*

As mentioned above, autistic people have difficulty in social and communicative settings. The lack of social skills and emotional understanding can prevent individuals with ASD of creating meaningful relationships with other people surrounding them as well as the difficulty in developing language skills and understanding how others communicate (NIDCD). It's important to consider the emotional suffering that these individuals can withstand, when studying the disorder. Difficulty of communication with people can often lead to loneliness that, consequently, leads to depression and anxiety. A study made at the General Psychiatric Hospital in 2013 analysed suicide attempts in ASD individuals against non-ASD individuals with depression and anxiety. Individuals with ASD were more likely to commit suicide, due to their impulsive behaviour and pre-mental conditions. (Kato, K. et al., 2013). Exploring the benefits of how an early diagnosis can have an effect in the lives of autistic people, could eventually save them as well.

Depending on the focus, autism can currently be diagnosed from a range of methods. Firstly, it's noteworthy to consider the origin of the disorder in itself. Throughout the years, the brain of an individual with autism has proven to have a different development than non-ASD individuals. Studies have shown that, most of the times, this development is influenced through genetic and environmental factors (Park et al., 2021). One can define environmental factors as influences in the individual's DNA when developing. Some to have in account include prenatal, peri-natal and post-natal infections, like exposure to certain viruses such as rubella and cytomegalovirus (Faras et al., 2010), low birth weight in woman and the appearance of auto-immune diseases (Park et al., 2021). When screening a child for autism disorder, gene defects and chromosomal anomalies are often found, due to these factos, making it important to study the interactions between both of these environmental and genetic factors, since it can lead to optimal treatment of the disorder (Park et al., 2021). However, Beary contested, saying that, despite being a genetic disorder, autism is more efficiently diagnosed to its distinct behavioural attributes (2020). Consequently, screening the population for early signs ASD typical behaviour is the first step to identifying the disorder in children, normally followed by the recommendations of primary care clinicians and earlier interventions (Hodges, et al., 2020).

As mentioned above, some early signs of autism in infants include irritability, difficulties with sleeping and eating, as well as some language delay (Park et al, 2021). Although, only at 3 years old, do ASD symptoms start to really manifest, such as lack of communication, repetitive behaviours, avoidance of eye contact and social interaction impairments (Faras et al., 2010). Recognising these symptoms early on, leads to early intervention which has been proven to be very beneficial when it comes to autism treatment (Corsello, 2005). Early intervention programs for children could benefit the lifestyle of autistic people, later in life. These interventions are often behavioural and developmental. Corsello studied how behavioural interventions focused more on teaching communication to autistic children, where developmental interventions focused more on developing skills and attributes, focusing on adapting the environment around for the child. Children demonstrate an acquisition of better gains, such as communication and developmental skills when completing a program starting from a young age. As seen above, the benefits of early intervention are clearly evident in children with autism and it's worthy to invest in early diagnosis.

Although, due to children's social and communication impairments, it becomes difficult to understand if certain behaviours are due to ASD or other environmental factors (Yates, 2016). It can be that certain diagnosis processes are too "by the book" and diagnose children wrongly. Thus, there should be investing in other methods of diagnosis, preferably less biased.

5.2 Importance of facial analysis

It was previously mentioned that autistic people contain altered genes that are, indeed, part of the cause of their disorder. Some studies have proven that these genes affect early brain development of people with autism. Since the face and brain are connected, the further in development can affect the facial feature development as well.

A study on whether children with autism develop different facial features than typically developed children was conducted in the University of Missouri (Aldridge, et al. 2011). The study analysed 105 boys between the ages of 8 and 12, where 64 boys had ASD and the remaining 41 were typically developed (TD). The boys were recorded using a 3D camera, where 17 points of the face were mapped and compared. Aldridge discovered that boys diagnosed with ASD demonstrate a significant difference in facial morphology compared to TD boys. Boys with autism were associated with a broader upper face with wide-set eyes, a middle region of the face and a broader or wider mouth. It was concluded that boys with ASF have an altered developmental pattern of facial features, derived from embryologic brain development.

In 2006, Golarai et al. studied how brain regions connected with social cognition and face processing, such as the superior temporal sulcus (STS) and the fusiform face area (FFA), correlate with face processing impairments in autistic individuals. Golarai found that early anomalies in gaze behaviour might lead to long-term face processing deficits.

Finally, in 2019, a study on cranio-facial characteristics in children with ASD was conducted, where two craniofacial markers related with autism severity were discovered in autistic patients: an increased orbital hypertelorism and a decrease of height of the facial midline (Tripi et al., 2019).

As a result of these studies, there is plenty of evidence to support that children with autism tend to develop different facial features than typically developed children. Hence, due to their common facial features, identifying and diagnosing patients with autism by analysis their facial features is the most efficient way to predict an autism diagnosis (Beary et al., 2020).

5.3 Machine Learning and predicting medical diagnosis

Machine Learning (ML), as a subfield of Artificial Intelligence, finds patterns in large amounts of data by utilising computer algorithms. These algorithms look for combinations in the chosen dataset and are able to reliably predict outcomes (Obermeyer, Z. et al., 2016). For this reason, ML has become an important tool for possible prediction of medical diagnosis.

In 2018, Chieh-Chen Wu conducted a study on the prediction of fatty liver, evaluating several classification algorithms (Wu, C-C, et all., 2018). ML proved to be efficient in the prediction of said condition, using minimal clinical variables. A prediction of ASD study was conducted as well, at the department of paediatrics, in the United States (Parikh, 2019) as well as a prediction of ASD using Deep learning (Beary et al., 2020). Both are conditions that can be evaluated using classification algorithms, since its diagnostic simply consists in saying if the patient has it or not. This study proved to be accurate in the prediction of ASD, using nine classification models.

5.3.1 Data as an obstacle

Considering the above studies, it's safe to assume that ML has proven efficient on predicting a medical diagnosis. So, it imposes the question of why this computational process isn't being implemented in medicine in its full. The point of ML as a prediction method would be to deposit the data and let the processes occur. According to Chen and Ash (2016), ML can indeed improve the accuracy of prediction using models but if there is no data to work with, it's useless. However, clinical data can often be misleading and lacking.

ML algorithms often require a higher amount of data to reach a proper conclusion, but data quality and quantity is often an issue when it comes to testing models. Data collection can be often biased, altering the performance and disrupting generality (Obermeyer et al., 2016). People with ASD often have certain genetic attributes to predict the condition, but not all individuals get tested for these attributes. So, in a certain dataset, not all participants are going to have the same attributes. Data needs to be cleaned and sometimes important things have to be discarded for lack of information.

When imposing cleaned data in a Machine Learning model, it can facilitate predictions but there is also the possibility of variations, that accumulate, making the prediction accuracy lower than pretended (Chen and Ash, 2016). As Chen and Ash mentioned in their article, "a better prediction is never going to equal a better clinical care". However, a better prediction might equal an earlier care, which, for people with Autism, for example, is beneficial when it comes to treatment.

5.3.2 Benefits of ML in the medical department

As analysed in the chapter above, data seems to be the worst issue when it comes to Machine Learning predictions and one can assume the medical community is sceptical on full implementation of computation processes for diagnosis prediction due to those problems. But with a clean and accurate dataset, ML can be extremely beneficial. As Obermeyer (2016) mentioned in his article, ML will dramatically improve prognosis compared to current prognostic models, such the Acute Physiology and Chronic Health Evaluation [APACHE] score and the Sequential Organ Failure Assessment [SOFA] score. These prognostics are dependable on direct human labour to input and tally scores whereas with ML, it's all produced by algorithms. ML allows the possibility of hundreds of variables for a more accurate score and these better estimates can help improve lives. Referring to Wu's study (2018), predicting a fatty liver in patients will help with early treatment, since patients can reduce the amount of alcohol consumed from an early age, for example, giving back years of life. The study coupled multiple variables like age, possibility of liver cancer, that helped predict the condition.

Besides improving prognosis, ML can also alleviate human work labour when it comes to data analysis. Interpreting digitalized images part of enormous datasets can be left to algorithms and prediction models rather than actual people. This implementation of computational processes in analysis not only saves time as it can improve performance since machine learning accuracy can easily exceed humans (Obermeyer et al., 2016). Humans make mistakes, and there's often diagnostic errors and no intervention to change to reduce them. Machine Learning comes to play, forming new diagnostic methods, reducing testing methods, which is beneficial for patients, removing pain and hassle. Although, there are still many variables that come to play when it comes to diagnosis. Predicting a cancer diagnosis, or an autism diagnosis is easy if have two possible outcomes: the person suffers from this condition or not. However, when it comes to diagnosing actual conditions from the same spectrum, it becomes more biased and complicated for a machine. One can easily predict if the patient has autism or not from previous data exploration but classifying each patient in the spectrum as having "Asperger's" or "Autism" would more complex.

Having in account all the points made, predictive algorithms will not eliminate errors in medical diagnosis. However, the prediction can be accurate enough to allocate health resources, prioritizing certain patients and allowing the possibility of early treatment. Machine Learning as a solo diagnosis tool is still not possible having it account all its possible issues. However, "(...) combining machine-learning software with the best human clinician "hardware" will permit delivery of care that outperforms what either can do alone" (Chen and Ash, 2016).

5.4 Autism Classification

In the chapters above, it was recognized the importance of analysing the facial features of children, since it has been studied that children with autism develop different facial attributes. There was also noted that Machine Learning has proven to be beneficial on predicting a medical diagnosis in certain conditions. The question that remains is, how can Machine Learning be, possibly, used to predict an autism diagnosis?

5.4.1 Image Classification Algorithms and Convolutional Neural Networks

Image Classification is a great part of Machine Learning. Image Classification algorithms are given a set of images labelled with categories as input, where training occurs and then the models are given a different set of images and are asked to predict the categories where they belong, measuring the accuracy of the predictions as well (Le, 2018).

One example of a model for image analysis and classification are Convolutional Neural Networks (CNN). A CNN model specializes in processing data that has a grid-like topology, such as an image (Mishra, 2020). CNN are really close to human brains, since its layers detect simpler patterns first and then more complex ones. There are already pre-trained models for image analysis, or one can create a CNN from scratch. In 2016, Liang conducted a study that aimed to prove that a Malaria diagnosis could be predicted by analysing only images. A pre-trained CNN model was applied to the dataset and a CNN model was also created based on that dataset to compare accuracy and performance. The CNN model creation was able to obtain an accuracy of 97%, 7% more accurate compared with the pre-trained model.

5.4.2 Transfer Learning

Transfer Learning refers to the process of applying a pre-trained network to a small dataset. A pre-trained network was previously trained on a large dataset, were obtained all the features to apply to smaller image classification tasks, proving useful for many computer-vision problems (Le, 2018). The benefit of transfer learning rather than creating your own model would be less risk of overfitting. Because the pre-trained model was trained using a large dataset and several features were acquired, it would be easier, on medical diagnosis since facial features are hard to come by, due to its immense detail, for example (Csefalvay, 2019). Complex problems could be supported in a more efficient way, since pre-trained models can decrease the training time for building a new learning model and finally improve its generalization performance (Tsiamaki, 2020)

However, transfer learning can also result in negative transfer. Negative transfer is when transfer learning actually decreases the performance of a model rather than improving it. This can happen if the datasets or image classification problems aren't at all similar, so there's something to be attentive to. Although, study made in 2019 concluded that negative transfer seems to be mostly related to specific algorithms and techniques and can avoided (Zang, 2019).

For this reason, both methods are going to be explored in the autism diagnosis prediction process, as it can be seen in methodology.

6 *Methodology*

In order to test the thesis being discussed, Machine Learning was applied to a dataset related to autism. Three image classifier models were created using the chosed dataset, whereas two of the models suffered from transfer learning from two pre-trained models: MobileNetV2 and ResNet50. These two methods are going to be compared for accuracy and performance when it comes to an autism diagnosis. All the code developed will be on a Jupyter Notebook, using Python. All the code developed was based on TensorFlow's notebook "Transfer Learning" https://www.tensorflow.org/tutorials/images/transfer_learning) and "Image Classification" (https://www.tensorflow.org/tutorials/images/classification).

6.1 Dataset

The dataset used for this experience was obtained from Kaggle, where it contains 2,938 children's facial images, where half of the facial images correspond to children with Autism and the other half to NonAutistic children. According to the author of the dataset, the images were gathered from the internet, through Google search, since there was the only way to obtain them. Since the images are not the best quality or consistency when it comes to facial alignment, the author implemented methods of processing and cropping, in order to better analyse the faces of the children. There was no independent search to figure out if the images are trustworthy or not. The dataset comes in .csv file, where it contains three folders named "training", "test" and "valid". The overall data composition can be observed in Table 1.

Dataset	Data size
Training	1,269 autistic 1,269 non_autistic
Testing	100 autistic 100 non_autistic
Validation	100 autistic 100 non_autistic
Total	2,938

Table 1- Dataset Information

6.2 Data Pre-processing

6.2.1 Dataset Split

Before training any CNN model, the data had to be processed for accuracy purposes. First step was to prepare the datasets for training. Observing the dataset, there are three separate files with images of autistic and non-autistic children. Three datasets were created based on this dataset split. The training, the testing and the validation dataset. The training set was used to train the classifier, as the name implies. The testing set was used to access the performance of the model. Normally, the testing set is also used to tune and hyper adjust the parameters of the model. However, splitting was performed on the training set into an 80% training data, 20% validation data, to improve accuracy and decrease bias when imposing these parameters. Thus, the validation set. When the datasets were created, the batch size and image size were defined. The batch size corresponds to the number of training examples propagated through the neural network, at once. Using a batch size, less memory is used at once and the network is trained faster, since the weights of the neurons are updated after each propagation. However, using batch sizes can also imply less accuracy. The batch size was defined as 32 and the image size was defined with the values (180,180), corresponding to height and width.

6.2.2 Data Standardisation

Data normalisation standardizes the data by changing the values of numeric columns in the dataset by changing the range of numbers to a common scale, between [0,1]. Since neural networks use values from [0,1] instead of the [0, 255] RGB range, normalisation processes were applied to the data. This improves processing and helps with removing duplicates.

6.3 Transfer Learning vs Model Creation

Both processes were tested using the Keras API (https://keras.io/) combined with Tensorflow (www.tensorflow.org) python libraries. Tensorflow is an open-source Machine Learning platform. One can define it as an infrastructure layer of differentiable programming. TensorFlow has many benefits such as efficiently executing operations on CPU, GPU, is scalable on operations of many devices and can easily export programs to external runtimes (keras.io). Keras is an open-source deep-learning library written in Python. Keras is simple and efficient, allowing standard deep learning models to be defined, fit, and evaluated in just a few lines of code. It serves almost as a backend, which combined with TensorFlow, forming "tf.keras", produces better results and has better integration, forming a multi-backend library (Browniee, 2019). While Tensorflow works as a deep learning framework, joining it with *keras* allows for simplicity when it comes to developing and evaluating deep learning models.

6.3.1 Model Creation

To test whether Machine Learning is effective on possibly predicting an autism diagnosis, an image classifier model was created. TensorFlow's keras Sequential model was used as the base model.

The model created consists of 3 convolutional layers, followed by 3 max-pooling layers. In order to make correct predictions, one additional layer is added to our model, a Dense layer with 128 neurons. A dropout layer was also applied, to reduce overfitting (explained in transfer learning section). The final output was a binary classification of "autistic" or "non_autistic.", identified by "class_names". The model was then compiled with an "accuracy" attribute, to check the accuracy of each training epoch. After compilation, the model was trained with the training dataset and the validation dataset, using 10 epochs.

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
sequential_2 (Sequential)    (None, 180, 180, 3)       0
_________________________________________________________________
rescaling_1 (Rescaling)      (None, 180, 180, 3)       0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 180, 180, 16)      448
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 90, 90, 16)        0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 90, 90, 32)        4640
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 45, 45, 32)        0
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 45, 45, 64)        18496
_________________________________________________________________
max_pooling2d_5 (MaxPooling2 (None, 22, 22, 64)        0
_________________________________________________________________
dropout_1 (Dropout)          (None, 22, 22, 64)        0
_________________________________________________________________
flatten_1 (Flatten)          (None, 30976)             0
_________________________________________________________________
dense_2 (Dense)              (None, 128)               3965056
_________________________________________________________________
dense_3 (Dense)              (None, 5)                 645
=================================================================
Total params: 3,989,285
Trainable params: 3,989,285
Non-trainable params: 0
_________________________________________________________________
```

Figure 1 - keras.sequential model

6.3.2 CNN Transfer Learning

To test whether Machine Learning is effective on possibly predicting an autism diagnosis, two models created using transfer learning with two pre-trained models: ResNet50 and MobileNetV2. Both of these models were trained using *keras API* and TensorFlow Python libraries, as well
Transfer learning allows to speed up training in a model, since pre-trained models, that contain classification model training already.

6.3.3 ResNet50

The model applied was ResNet50, developed by Google. ResNet50 gained the ImageNet challenge in 2015 for its efficiency in speed and efficiency when training +150 layers successfully.

```
Model: "model"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_4 (InputLayer)         [(None, 160, 160, 3)]     0
_________________________________________________________________
sequential_1 (Sequential)    (None, 160, 160, 3)       0
_________________________________________________________________
tf.__operators__.getitem (Sl (None, 160, 160, 3)       0
_________________________________________________________________
tf.nn.bias_add (TFOpLambda)  (None, 160, 160, 3)       0
_________________________________________________________________
resnet50 (Functional)        (None, 5, 5, 2048)        23587712
_________________________________________________________________
global_average_pooling2d_1 ( (None, 2048)              0
_________________________________________________________________
dropout (Dropout)            (None, 2048)              0
_________________________________________________________________
dense (Dense)                (None, 1)                 2049
=================================================================
Total params: 23,589,761
Trainable params: 2,049
Non-trainable params: 23,587,712
_________________________________________________________________
```

Figure 2 - resnet50 model

6.3.4 MobileNetV2

The model applied was MobileNetV2, developed my Google. MobileNetV2 is a type of Mobilenet, which is a CNN architecture that uses depth wise separable convolutions to construct lightweight deep convolutional neural networks, providing an efficient neural network model with several applications (Howard, 2017). MobilenetV2 is a pre-trained model, which means it was previous trained with a large image dataset, the ImageNet, containing 1.4 images and 1000 classes. Two different processes were applied when creating the model, for comparison.

```
Model: "model_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_3 (InputLayer)         [(None, 160, 160, 3)]     0
_________________________________________________________________
sequential (Sequential)      (None, 160, 160, 3)       0
_________________________________________________________________
tf.math.truediv_1 (TFOpLambd (None, 160, 160, 3)       0
_________________________________________________________________
tf.math.subtract_1 (TFOpLamb (None, 160, 160, 3)       0
_________________________________________________________________
mobilenetv2_1.00_160 (Functi (None, 5, 5, 1280)        2257984
_________________________________________________________________
global_average_pooling2d (Gl (None, 1280)              0
_________________________________________________________________
dropout_1 (Dropout)          (None, 1280)              0
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 1281
=================================================================
Total params: 2,259,265
Trainable params: 1,862,721
Non-trainable params: 396,544
_________________________________________________________________
```

Figure 3 - mobilenetv2 model

6.3.5 Methods

i) Feature Extraction

Feature Extraction works by adding a new classifier on top of the pre-trained model, using specific features from the pre-trained one. MobileNetV2 was pre-trained with another image dataset, there were some layers not relevant to the data. The top classification layer of the model is very specific to the original classification task, as in, the original dataset the model was trained, containing the classes from previous dataset. So, this layer was frozen and not used, and a new classification head was put on top instead and trained for specificity on the autism dataset currently in used. This method of freezing was performed before compilation and training of the model, to prevent weights of the last layer to be updated. That layer needed to be excluded immediately.

ii) Fine Tuning

To add to the feature extraction and improve performance and accuracy, fine tuning procedures were applied on the module. Fine Tuning a model means unfreezing the top layers of the pre-trained model, add new classifier layers and train both, simultaneously. This makes the new model more relevant to the task being performed, excluding possible generalities. If the weights weren't frozen in the beginning, the pre-trained model, MobileNetV2, would "forget" all the knowledge it started with because the new classification head was initialized randomly. But since the classification head was already trained, the layers can be unfrozen to fine-tune the dataset (Cruz, 2019).

The top layers, previously frozen, were unfrozen and those weights were trained alongside the training classifier we added. This process will allow the tuning of the weights of the top layers, which will transform the generic features into specific features of the autism dataset, more specifically, the binary classification of "autistic" and "non_autistic". Only a few layers were trained alongside, since training the whole model could've resolved into overwriting of the generic learning MobileNetV2 brings (TensorFlow.org).

6.3.6 Overfitting

Overfitting is a common problem in Machine Learning and it can happen when large neural nets are applied on small datasets, like in this case. Overfitting can make the model learn statistical noise in the training data and perform badly when in front of new data, e.g. the training set (Browniee, 2018). To make sure this wouldn't happen, Data Augmentation and Dropout processes were applied to the model

i) Data Augmentation

As mentioned above, overfitting happens regularly when we apply small datasets to large CNN models. Data Augmentation works by adding additional training data to the dataset, using random transformations of current images. In 2017, a study on data augmentation was conducted on multiple datasets, showing the significant accuracy improvement on classification tasks. For a classification between cats and dogs, the training accuracy was up by 20%, when data augmentation was applied (Wang, 2017). Thus, three "Random" layers were added when creating the model, to improve our model's accuracy and performance.

ii) Dropout

Dropout is a regularisation technique that consists in training a large number of neural networks with different architectures in parallel. This works by randomly dropping layer outputs, which makes it seem like the layer has a different number of nodes, making it unpredictable. "Random dropout breaks up these co-adaptations by making the presence of any particular hidden unit unreliable" (Srivastava, 2014). The rate of dropout applied to our model was of 0.2 e.g., 20% of outputs were dropped.

6.4 Evaluation Criteria

To evaluate each models' performance, accuracy and loss of prediction of testing, validation and training is going to be considerate.

7 *Evaluation/Results*

7.1 Model Creation without Transfer Learning

After training of ~10 epochs, the models training accuracy reached a 72.6% and the validation accuracy reached a 70,9% as seen in Figure 1. The models training loss reached 53.7% and the models validation loss reached a 55,1%, as a mean, as seen in Figure 2.
Training took approximately 12 minutes.

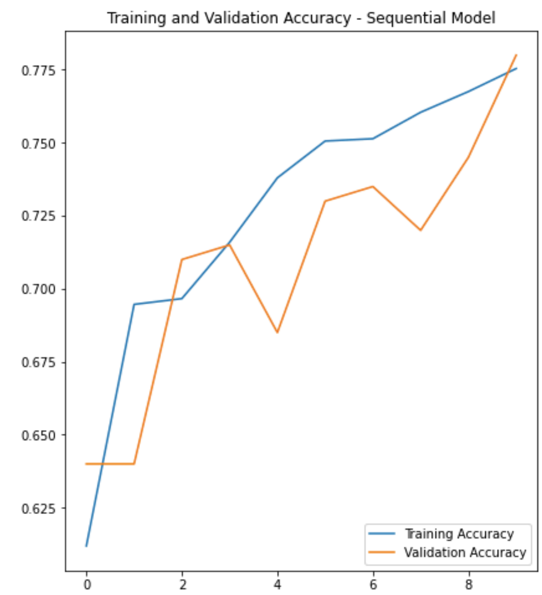

Figure 4 - sequential.model accuracy

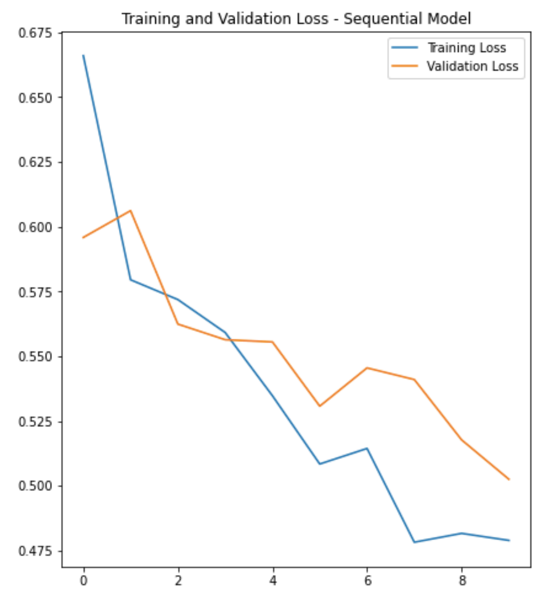

Figure 5 - sequential.model loss

After evaluating the model, the models testing accuracy reached a 92%, with only 18% loss.

7.2 Transfer Learning

7.2.1 ResNet50

After training of ~10 epochs, the models training accuracy reached 77,1% and the validation accuracy reached 75,6%. The models training loss reached 48,8% and the models validation loss reached a 53,7%, as a mean. After Fine Tuning was applied, training of the 15 epochs, training accuracy reached 81,5% and validation accuracy was upped to 80,6%. The training loss was reduced extremely to 37,8% and the validation loss was reduced to 43,5%. Evidently, accuracy increased approximately 5% and loss decreased by 10%.

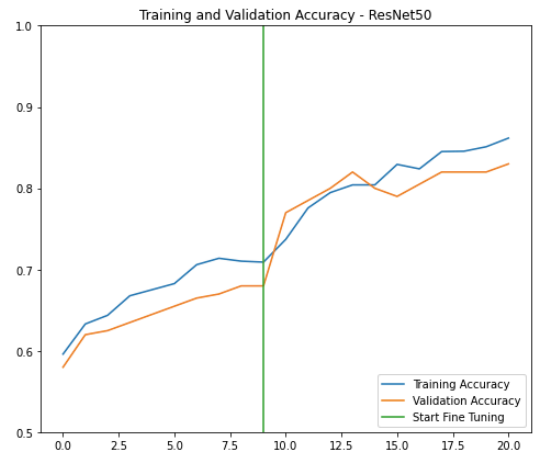

Figure 6 - resnet50 accuracy

Figure 7 - resnet50 loss

After evaluating the model, the models testing accuracy reached 87,5%, with only 27,3% loss. Training took approximately 30 minutes.

7.2.2 MobileNetV2

After training of ~10 epochs, the models training accuracy reached a 70,5% and the validation accuracy reached a 67,3%. The models training loss reached 54.1% and the models validation loss reached a 57,4%, as a mean. After Fine Tuning was applied, training of the 15 epochs, training accuracy reached 72,7% and validation accuracy was upped to 69,1%. The training loss was reduced to 51,3% and the validation loss was reduced to 55,5%. Consequently, accuracy improved by almost 3% for training and validation and loss decreased reduced by almost 3% as well.

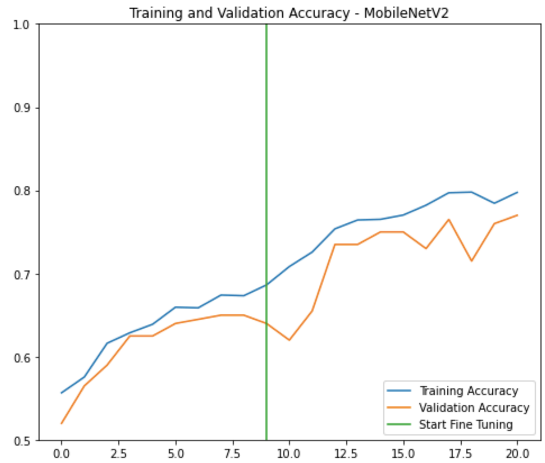

Figure 8 - mobilenetv2 accuracy

Figure 9 - mobilenetv2 loss

After evaluating the model, the models testing accuracy reached 83,5%, with only 36,7% loss. Training took approximately 30 minutes.

As can be seen for both models, after Fine Tuning was applied, the accuracy improved by almost 3% for training and validation. In the graphs above, there's a visible change on the curve after fine tuning was implemented in the model.

7.3 Evaluation of Results

Model	Training Accuracy	Validation Accuracy	Testing Accuracy	Training Loss	Validation Loss	Testing Loss
Keras.Sequential	72,6%	70,9%	92%	53,7%	55,1%	18%
ResNet50	81,5%	80,6%	87,5%	37,8%	43,5%	27,3%
MobileNetV2	72,7%	69,1%	83,5%	51,3%	55,5%	36,7%

Table 2 - Results

As observed in the table above, the model who performed better overall was ResNet50. Although creating the model with *keras* API achieved a testing accuracy of 92%, being the highest, ResNet50 overall accuracy compared to the other models was higher, including training and validation. ResNet50 also presented to have the less loss percentage, comparing to the overall of the other models.

8 *Discussion*

The purpose of this study was to prove that Machine Learning could indeed be effective at predicting an autism diagnosis, based on facial analysis. Training and testing of different CNN models with a dataset containing pictures of children with autism and children without, enabled the binary classification of images on either "autistic" or "non_autistic". All the ML models trained reached an accuracy of approximately 85% on predicting the autism diagnosis when testing it with new data, where the model trained with ResNet50, performed its overall best, compared with MobileNetV2 and own model. However, the model trained with the dataset, not using transfer learning to aid the training process, performed best in the testing, reaching 92% accuracy.

Machine Learning, using classification algorithms, has been proven effective in the prediction of medical diagnosis before. For example, in 2018, ML was able to predict a fatty liver diagnosis, using just classification models such as artificial neural networks (ANN), logistic regression (LR) and random forest (RF) (Wu, C-C, et al., 2018). This inspired the possible prediction of different diagnosis, like autism. Following, in 2020, Beary et al. (2020) performed a study on the prediction of ASD, using transfer learning with MobileNetV2. The classifier created in this study was able to achieve 94,6% accuracy. This study influenced the study of autism using neural network classification models. However, Beary studied the performance of one model, whereas this study was conducted using three classification models. Not only there's a better perspective of which one performed better, but if the results are consistent across different models, Machine Learning's efficiency can be tested in a more accurate way.

Using the same dataset as Beary et al. (2020) and MobileNetV2, the testing accuracy achieved was of 82%, slightly lower than Beary's study. This might've been due to using different layer values or data formats. For example, a Dropout layer was added to our model, to prevent overfitting, at a 0.2, whilst in Beary's study, it was 0.4. Using a different neural network, ResNet50, the accuracy was of 87,5%, slightly higher. But the best performance, was when the model was trained with the dataset, specifically for autism facial features, achieving 92% accuracy, closer to Beary's result. As can be seen, the model that performed better was the one that wasn't created using transfer learning and trained directly with the dataset.

The results of this study highlight the difference between using transfer learning and not using it, when creating a classification model for prediction. Referring back to Liang's study, in 2016, on predicting Malaria diagnosis using Convolutional Neural Networks, there is a concordance in values. Liang studied the performance of a model created using transfer learning and of one without. Here, the model without, also performed better than the one created using transfer learning, achieving 97,37% of classification accuracy. This can mean that negative transfer occurred, since the pre-trained models are trained with a different dataset than the one to be tested. Nevertheless, the fact that the all the models tested achieved an accuracy above 80%, when predicting an autism diagnosis on new data, shows the efficiency of Machine Learning on prediction of the diagnosis.

Some limitations of this study refer back to data collection. As mentioned in the Methodology chapter, the dataset used for this study was obtained from Kaggle. The author gathered the images from Google Search, without any background check on the validity of images. So, images labelled as “autistic” or “not autistic” in the dataset used, might not be entirely true. This puts in cause the validity of the models created, since the models were trained with data that might be misleading. Referring back to Aldridge’s et al. (2011) studies on facial analysis in autistic people, it’s important to refer that autistic children do develop different facial features from people. However, to train our model to predict accurately if children had autism or not, the initial data had to be proven medically before. For future training of models, an official dataset would be recommended. Thus, ethical issues have to be considered since official and proven information might want to stay private.

Another limitation found was the data size and content. Referring their article on Machine Learning, Chen and Ash (2016) mentioned the importance of cleaning data. Getting rid of duplicates and again, double-checked, would help improve overall accuracy. However, this wasn’t possible due to lack of experience in the medical field. Data size could’ve possibly influenced the accuracy. The models were trained on a 2,938-subject dataset, which is relatively big for a clinical study on a neurodevelopmental disorder. However, larger datasets could be considered to create models that allow for a bigger generalization of diagnosis.

Also, the models in question are limited on an autism diagnosis. Although, the question on efficiency of Machine Learning on predicting an Autism diagnosis was answered, the models were only trained for this specific dataset with facial features. So, diagnosing Autism with other features would have to be done using another dataset. Although, it makes sense to separate image classification models from other features, such as speech or movement, since the models were built for that.

For future work, more classification models could be created using other transfer learning pre-trained models to create new image classification models. Although, the pre-trained models didn’t perform the best in this study, there are other models than can be implemented, like Inception or VGG. Part of the lack in accuracy, as mentioned, was data collection and processing, so a study on autism can be continued, gathering trustworthy data from people with autism for an accurate result.

As studied by Corsello in 2005, early intervention benefits people with autism. It allows focus on communication and behavioural issues from young, which can improve overall lifestyle. There are studies on autism diagnosis but it's an area that is still lacking in knowledge. Continuous study of Machine Learning on the prediction of this disorder, could potentially lead to creating a clinically approved model that can be implemented in the medical department.

Besides autism, these methods of creating Machine Learning classification models can be used to classify other disorders. ASD (Beary et al., 2020) and fatty liver (Wu, C-C, et all., 2018) were just some examples tested with classification models, but it's worth investing in Machine Learning methods for prediction, since, as mentioned by Chen and Ash, "(...) combining machine-learning software with the best human clinician "hardware" will permit delivery of care that outperforms what either can do alone".

9 *Project Management*

As a project management platform, Notion (Notion) was chosen. Notion allows for creation of to-do lists, tables, Kanban boards, Gant Charts and other ways for organization and planning.

9.1 Time Management

For a first draft, pre-plan the project, a time sheet was created, as seen as well as a Gant Chart, as seen in figures 11 and 10 These were included in the Project Proposal as initial Research Plan.

Figure 10 - Previous Gant Chart

TASK	START	END
Literature Review		
Autism	01/01/2020	14/01/2020
Affective Computing	15/01/2020	01/02/2020
Emotion Recognition Frameworks	01/02/2020	15/02/2020
Selection		
Programming Language Selection	16/02/2020	17/02/2020
Emotion Frameworks Selection	17/02/2020	25/02/2020
Dataset Selection	26/02/2020	04/03/2020
Process		
Analyse Data		
Perform EDA	04/03/2020	10/03/2020
Feature Extraction	10/03/2020	14/03/2020
Pre-Process Data	15/03/2020	20/03/2020
Framework Implementation		
Test and Train frameworks	20/03/2020	01/04/2020
Evaluation Results	01/04/2020	05/04/2020
Evaluation Reviews	05/04/2020	08/04/2020
Compare Frameworks	08/04/2020	14/04/2020
Review Comparison	15/04/2020	17/04/2020
Submission Preparation		
Results and Conclusions	17/04/2020	22/04/2020
Discussion	22/04/2020	25/04/2020
Future Work	25/04/2020	28/04/2020
Project Submission	01/05/2020	01/05/2020

Figure 11 - Previous time management

However, when actually starting the project, the main theme changed so the planning had to change to. The research question no longer involved Autism nor Affective Computing due its complexity in theme and it made more sense to incorporate Machine Learning algorithms into the research question. Besides that, time frames were changed since some chapters were going to take longer than planned.

A new Gant Chart and Table were created, this time in Notion, as can be seen in figures, 18 and 19. This method of time management allowed for a better visualisation of the project components and how much time they would supposedly take. The table allowed to oversee the progress of the task, the timeframe where it should be done and the chapter where it belonged. The Chart allowed to not only see the current chapters to be worked on but the chapters that followed, which allowed for planning ahead and making sure everything was on time.

To Do Table view

Task	Status	Property	Start
Autism	Completed	Literature Review	Jan 17, 2021 → Jan 31, 2021
Machine Learning	Completed	Literature Review	Feb 01, 2021 → Feb 08, 2021
Machine Learning and Medical Diagnosis	Completed	Literature Review	Feb 09, 2021 → Feb 16, 2021
Dataset Selection	Completed	Methodology	Feb 17, 2021 → Feb 20, 2021
Analyse Data	Completed	Methodology	Feb 21, 2021 → Feb 24, 2021
Train model with keras.Sequential	Completed	Methodology	Feb 25, 2021 → Feb 28, 2021
Train model with MobileNetV2	Completed	Methodology	Mar 01, 2021 → Mar 06, 2021
Train model with ResNet50	Completed	Methodology	Mar 07, 2021 → Mar 13, 2021
Evaluate Models on Accuracy	Completed	Methodology	Mar 14, 2021 → Mar 20, 2021
Write up Results	Completed	Results	Mar 21, 2021 → Mar 24, 2021
Write Discussion	Completed	Discussion	Mar 25, 2021 → Mar 29, 2021
Conclusion	Completed	Conclusion	Mar 28, 2021 → Mar 31, 2021
Introduction	Completed	Introduction	Apr 01, 2021 → Apr 03, 2021
Abstract	Completed	Abstract	Apr 04, 2021
Project Submission	In progress		Apr 30, 2021

Figure 12 - Current time management

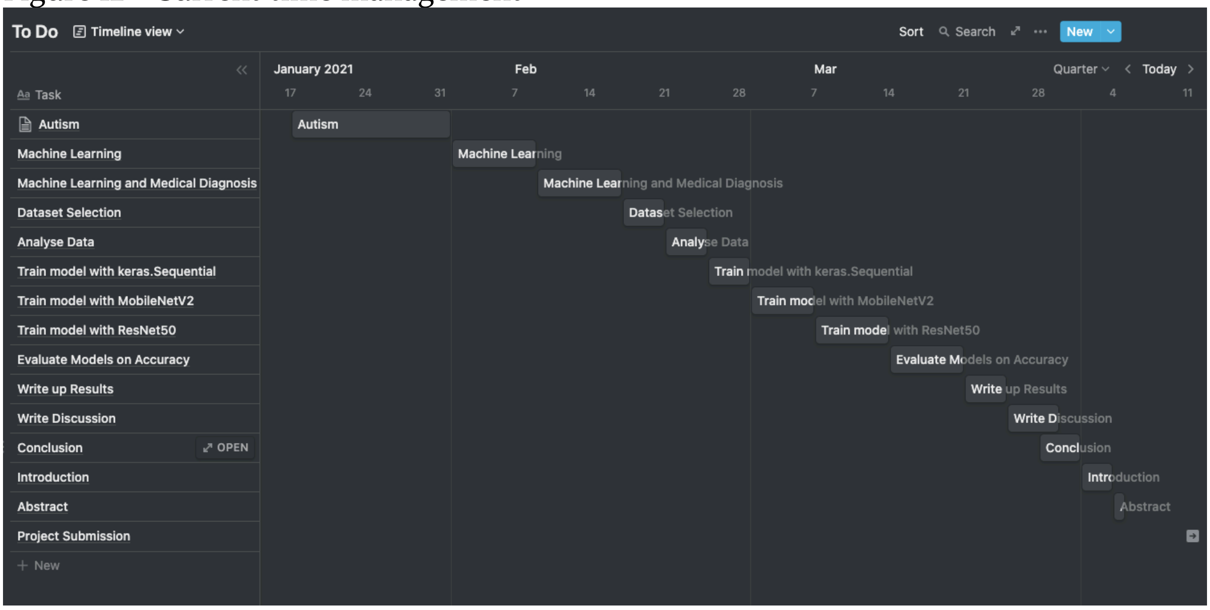

Figure 13 - Final Gant Chart

Besides initial research, a Kanban Board was created to keep track of tasks across the week. Kanban Board is a part of the AGILE Methodology, a popular task management tool. The board was created also in Notion. Kanban allows for a better visualisation of tasks in a central manner. As can be seen in Figure TAL, the tasks are divided into three subsections: “Not Started”, “In Progress” and “Completed”. The visualisation of the progress offers a better insight on how the project is flowing, as well as with each chapter.

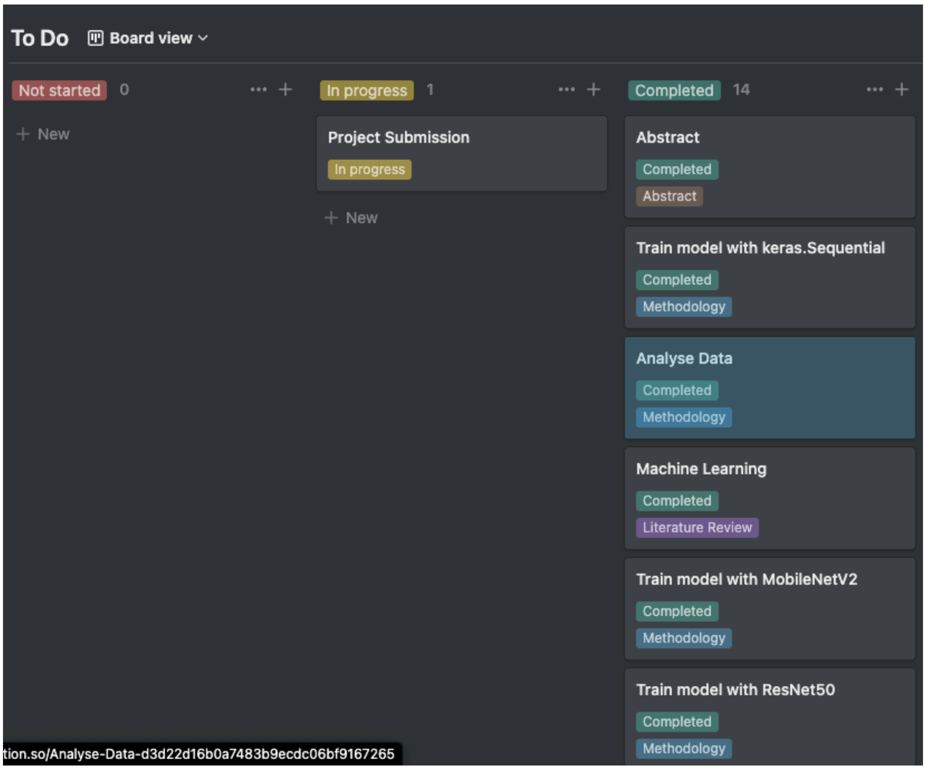

Figure 14 - Kanban Board

9.2 Ethical Considerations

As explained in methodology, the process of training and creating the models included the use of a dataset. When scouting for a dataset to use that included children with Autism, some considerations had to be made. First of all, the dataset obtained was secondary research, which means other people collected the data used for this research. Obtaining data as first research was considered, but there were some implications. Lack of time was a big limitation. There was little to no time to communicate with children with autism and children without, take pictures of them and get consent to use them. Besides, privacy issues need to be considered when talking about people with a disorder. They might not want their face and their diagnosis to be known or studied.

Concerns around the secondary use of data include mostly potential harm to subjects. If data that is used has some kind of information that can lead to identification of the subjects, there has to be consent of each individual. However, the dataset created used photographs from children with autism and without, was taken from Google Search. If data is freely available on the internet, permission for further use and analysis is always implied (Prasad, 2013). However, this poses the issue of data being compromised. Although it was on the right format, the author did no background check on the pictures to see if they corresponded to people with autism or not. The data can be available but the uses for it might be invalid due to not being trustworthy. However, for this study, due to lack of resources and time, there was a need to use the dataset available. It was free of use and it was in a format that allowed for easy analysis and exploration.

9.3 Problems

Due to lack of time and overload of work, the project could not be completed as planned with the time management. Besides this dissertation, there were two other modules to complete in the author's University Course, on top of a part-time work, so the project had to be differed.
The project being differed alleviated a lot of pressure of the author and it could be completed more smoothly.

There was not a lot of communication with the supervisor due to, again, lack of time. A feedback on literature review was asked and it was really helpful for the structure and organization of the chapter. Since the project had to be completed in a short amount of time, there was no room to ask for help on each chapter. However, the author asked for help when it was possible and was able to finish the project on time.

10 Conclusion

It can be concluded that Machine Learning was effective at predicting an Autism diagnosis. Autism is a disorder that can affect people throughout their lives, if not diagnosed early. Early intervention would help children with autism cope better with their social and communication impairments, in order to live better lives. So, it's important to diagnose patients at a young age, in order to provide early treatment. However, some diagnosis methods like screening can be biased since some characteristic in children might not originated from ASD but from environmental factors, for example. Due to developing different facial features, children with autism can be diagnosed through analysing them. Hence, the image classification models created in this study, were helpful when diagnosing children more accurately.

From analysing the results, all three models performed with an accuracy of above 80%, where the highest accuracy achieved was of 92%, from the model trained with an Autism dataset, meaning there was a possibility of distinguishing a child with autism from another without, by simply analysing their facial features. This accuracy could've improved if the data used accurate as well. Since the dataset used contained images taken from Google Search, making the data not trustworthy, this could've made the created models invalid. The data could've also been cleaned and prepared.

In terms of methodology, the model that showed to be more accurate in the prediction was the model trained with the dataset only, not utilising features from other datasets. Of the three models created, two used the method transfer learning. Transfer learning can be beneficial to prevent overfitting but, in this case, training the model directly with the dataset, achieved more accuracy due to building the model around those specific features. Consequently, it can also be concluded that creating a model from scratch, can be more effective on prediction as well. Nevertheless, since all the models achieved at least 80% accuracy when testing, it allows to conclude that Machine Learning can indeed be effective at predicting the autism diagnosis.

The models created can be beneficial when creating an autism diagnosis and its accuracy can be improved. For future work, its recommended to use a different dataset, one clinically proven, for more accurate results which might mean the inclusion and use of these algorithms in the actual medical field. This work can be continued and improved, in order to improve the diagnosis method of people with an Autism disorder. Machine Learning has proven to have a lot of potential in the medical field, by alleviating human work labour and performing more accurately when it comes to analysis purposes. It stands obvious that life is not linear, and people can always be wrongly diagnosed when there's only one spectrum working. However, combining

Machine Learning with our current human work can eventually create more efficient diagnosis methods, improving people's lives.

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