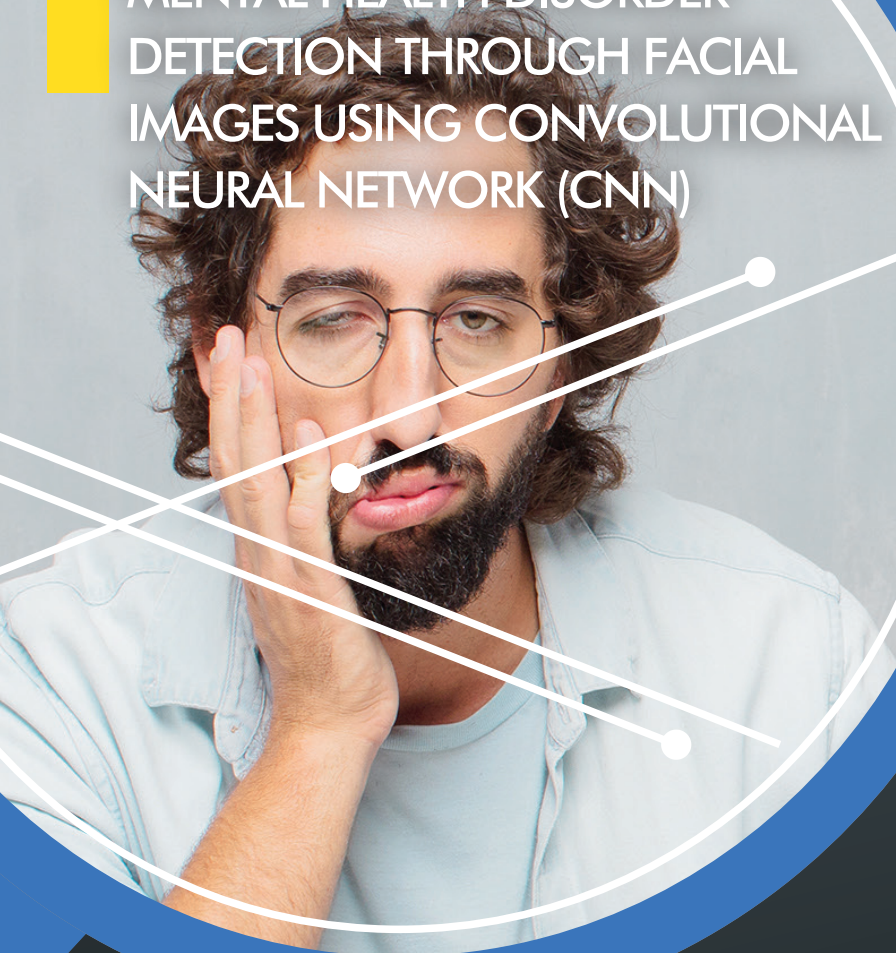


Digitimes #33
NOVEMBER 2020

MENTAL HEALTH DISORDER DETECTION THROUGH FACIAL IMAGES USING CONVOLUTIONAL NEURAL NETWORK (CNN)



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NOVEMBER 2020

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■ ABSTRACT

Mental health disorder is often concealed due to social paradigms in some regions due to the impact of one's well being and image. Therefore, many individuals conceal their mental disorders and lead to the worsening condition of their mental health. (Venkataraman and Parameswaran, 2018) Detection of mental illness proves to be difficult when concealed, but research by Ward and Scott (2018) implicates the possibility of performing detection on neutral faces. This research aims to create CNN models that implement transfer learning methods with base models VGGFace2 and InceptionV3 due to the scarcity of dataset. The implementation of the program augments the data to create a dataset of 336 images from resizing, flipping, photometric transformation, and face averaging. The pretrained models are trained over 20, 30, and 40 epochs using Adam and Stochastic Gradient Descent optimizers using K-Fold validation scheme. The best models produced 0.9762 and 0.66 average accuracy for VGGFace2 and InceptionV3 respectively. Finally, the research analyzes the models' decisions using the LIME explainer library. The models expressed regions of interest on the area of the mouth, the eyes and nose when predicting high tendency of mental disorder, while outer regions are considered to support prediction of low tendency of mental disorder.

Keywords: Convolutional Neural Network, VGGFace, InceptionV3, Mental Health Disorder Detection, LIME Explainer



■ GLOSSARY

Mental Disorder: is a subset of health disorder that may be associated with one or more forms of functional disadvantages (Luxton, 2018). Various symptoms of different mental disorders are available in the Diagnostic and Statistical Manual of Mental Disorders (DSM), and is used for psychiatric diagnosis.

Artificial Neural Network: Artificial Neural Network (ANN) is a machine learning paradigm that loosely mimics the behaviour and structure of biological neural networks. It simulates the firing and blocking of neurons using binary values 0 and 1. Modern application of ANN may amplify input values repeatedly in a statistical system to produce outputs (Luxton, 2018).

Convolutional Neural Network architecture: Convolutional neural network (CNN) is an architecture paradigm of deep neural networks that extends the layers of an ANN. CNN further imitates neurological systems by adding layers that have similar function to the visual cortex.



Convolution Layer: A convolution layer contains k learnable filters with size $(a \times b \times c)$, and have them compute the dot product of the values across the input features with restricted area $(a \times b \times c)$ to produce outputs with size corresponding to its filter properties. In image classification, the convolutional process allows models to learn the correlation between a pixel of information and its neighbouring pixels (Li and Deng, 2018).

Pooling Layer: Pooling layer is used to further reduce the computation time by summarizing the feature map that is produced by the convolution layer. It is done by traversing a window of size $(a \times b)$ across the feature map with size $(W \times H)$ and perform either max, average, or min function to produce an output with size $(W - a \times H - b)$ with the assumption of stride = 1.

Fully Connected Layer: The fully connected layer (FCL) essentially ensures that the features that are produced in the previous layers are connected to the nodes in the ANN.

Stochastic Gradient Descent: Gradient descent is an optimization algorithm with an objective to find the minimum value of a function, which in case of machine learning models is the cost function.

Hyperparameter: Hyperparameter refers to sets of parameters in machine learning models that determine the network structure and functions. While hyperparameters such as number of nodes and numbers of layers affects the structure of the network, hyperparameters such as learning rate and activation function affects the value of information that flows in a network.

Transfer Learning: Transfer learning is a technique in the field of machine learning in which a model is developed and trained to achieve a certain task and then used in another related task. Given that the weights are optimized by training the model in a preset setting as opposed to starting the initial training from random weight in, it is expected that the model could achieve a certain degree of success in accomplishing a task.

VGGFace: VGGFace is a pre-trained model that has been trained against over 2 million faces (Parkhi et al., 2015).

Resnet50: In resnet50 architecture, residual blocks are used to map the identity function by pushing the residuals to zero instead of trying to fit the stack of non-linear layers to a certain identity function.





■ BACKGROUND

Mental health has been a concerning subject in Indonesia. In 2018, 1.7% of the approximately 264 million Indonesian population are recorded to suffer severe mental disorder, while 9.162.886 cases of depressive disorders and 8.114.774 cases of anxiety disorders are reported according to Global Burden of Disease study 2015 as referenced in 2017 World Health Organization global health estimates (Hartini et al., 2018; World Health Organization, 2017). Despite the numerous severe cases of mental illness recorded, stigmatization and negative views still exist among the society.

The prevalence of stigmatization of mental health in Indonesia is evident from various forms of discrimination by the society towards subject of mental health disorders. One extreme form of

discrimination that borderlines torture involve the still existing case of *pasung*, or stocks in the English language, in which the subject of mental disorder is fixed to a certain object to restrain movements. Stigmatization also has an effect on subjects with symptoms of mild mental health disorders. In a 2018 Jakarta Globe news article, stigmas affect the sufferers of mental disorder in a way that subjects suppress their mental disorder for the fear of persecution by the society that would affect their social and economic interactions (Baskoro, 2018). The suppression of such conditions result in refusal of subjects to receive treatment from professionals, worsening their conditions. Hence, this research aims to further the potential usage of technology in aiding this concern.



ARTIFICIAL INTELLIGENCE AND PSYCHOLOGY

Initial artificial intelligence studies involve machine learning algorithms that employ mathematics to correct itself. The rise of computing power and memory capacity have enabled machine learning algorithms that were initially invented in the 1950s to 1980s (Meek, 2018). This form of enabling has given birth to various applications of artificial intelligence (AI) in different fields and industries, including the field of psychology. In fact, AI has been used as a decision support system by healthcare professionals to diagnose and make decisions by learning the preferences and patterns of a subject (Luxton, 2018). In his book, Luxton (2018) compiled research regarding AI and its usage in regards to mental health to respond and demonstrate the emerging technologies in the matter. In fact, competitive accuracy on emotion recognition that employs artificial intelligence using facial features recognition are researched and competed upon, showing the potential of facial features and expressions in various classifications (Li and Deng, 2018).

In his research, Ward and Scott (2018) performed a survey research on the evaluation of mental health disorder through facial image with neutral expression. Although major facial features have not been identified, the result further suggests correlation between facial images and its perceived mental health evaluation. Morphological researches in this particular domain in the field of computer science do not exist yet due to the recentness of the research itself in the field of psychology. Several methods such as local binary pattern (LBP), Histogram of Oriented Gradient, and Support Vector Machine (SVM) have been attempted to analyze mental illness through non-neutral facial expressions (Deshmukh and Fadewar, 2017). The same method has not been used on a dataset of faces with neutral facial expressions that would be useful to detect signs of mental disorder from faces of subjects that suppress their symptoms.

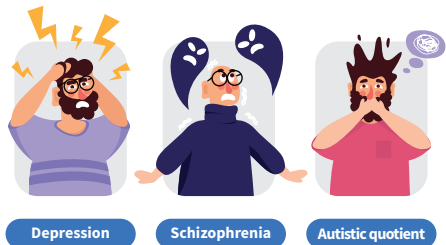


These kinds of image classification problems have been one of the main problems in the field of Computer Vision with a variety of practical applications Hussain et al. (2019). The approach of convolutional neural networks (CNN) has been proven to be one of the successful models to solve classification problems due to its superior performance Bochinski et al. (2017). However, problems arise in cases of small dataset, where the data itself is scarce due to reasons such as confidentiality. The abstract construction of CNN filters, i.e. non hand-picked features, that is faced with a small dataset will bottleneck the performance of the model. To address this problem, Hussain et al. (2019) evaluates the effectiveness of transfer learning method in using pretrained models to initialize another model that has similar task. In cases where sensitive information is involved in the dataset (hence the small size), e.g. facial images with annotated mental health diagnosis, transfer learning could prove to aid boost the performance of a model.

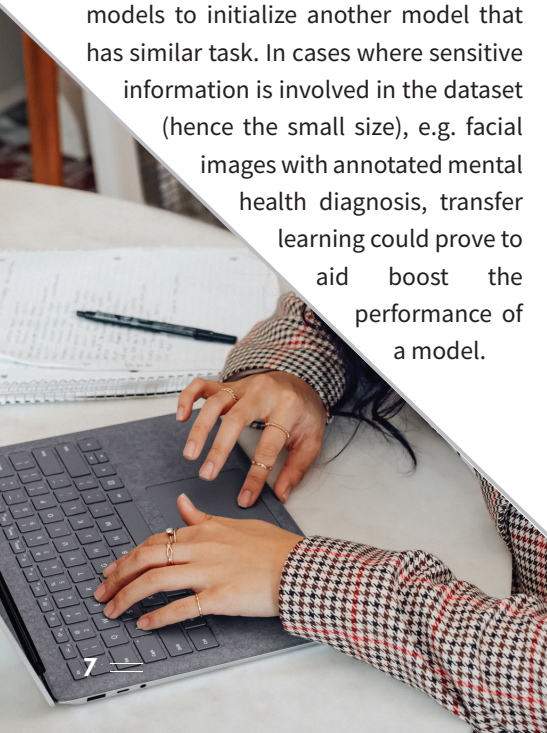


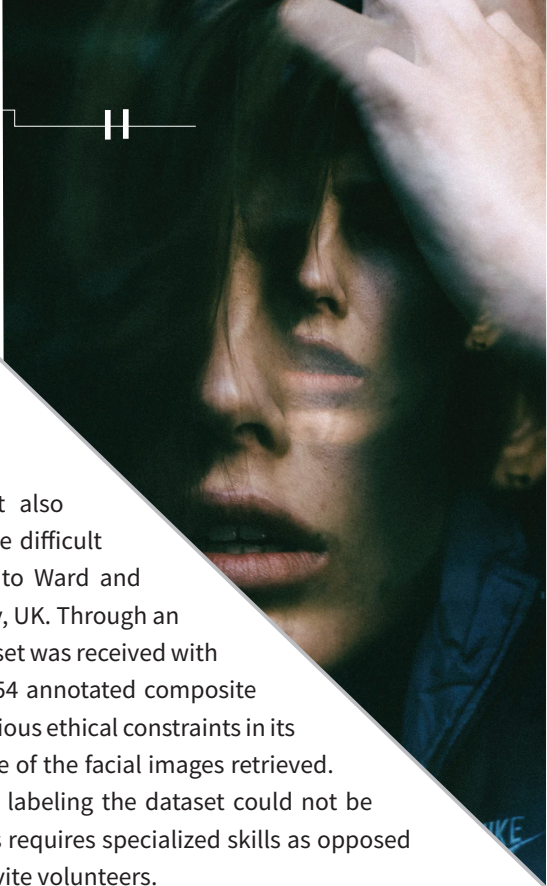
■ RESEARCH SCOPE

The facial image dataset retrieved from Bangor University's Robert Ward will be used. The images in the dataset consists of composite facial images of subjects diagnosed with high and low mental health disorder. The faces in the image will be of neutral expression. Due to constraints of the dataset, the models will strictly be trained on images of Caucasian males. Three different labels of mental disorder are present in the dataset, they are:



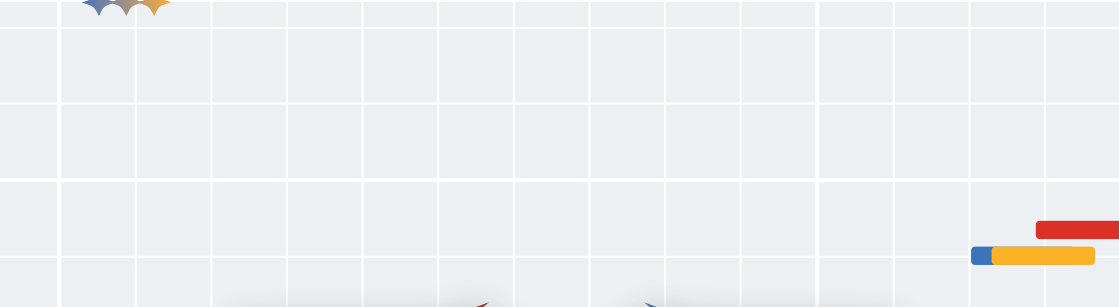
Generalized mental disorder will be evaluated, as the 3 will be reduced in dimension to high and low tendency of mental health disorder.





■ DATA ACQUISITION

Since mental health records that also have the subjects' facial images are difficult to collect, a dataset is requested to Ward and Scott (2018) from Bangor University, UK. Through an electronic mailing system, the dataset was received with its annotation remarks. A total of 54 annotated composite facial images was obtained with various ethical constraints in its usage. Figure 4.2 shows an example of the facial images retrieved. Without professional qualification, labeling the dataset could not be done since psychological diagnosis requires specialized skills as opposed to general knowledge that could invite volunteers.



**High Tendency of
mental disorder**

**Low Tendency of
mental disorder**

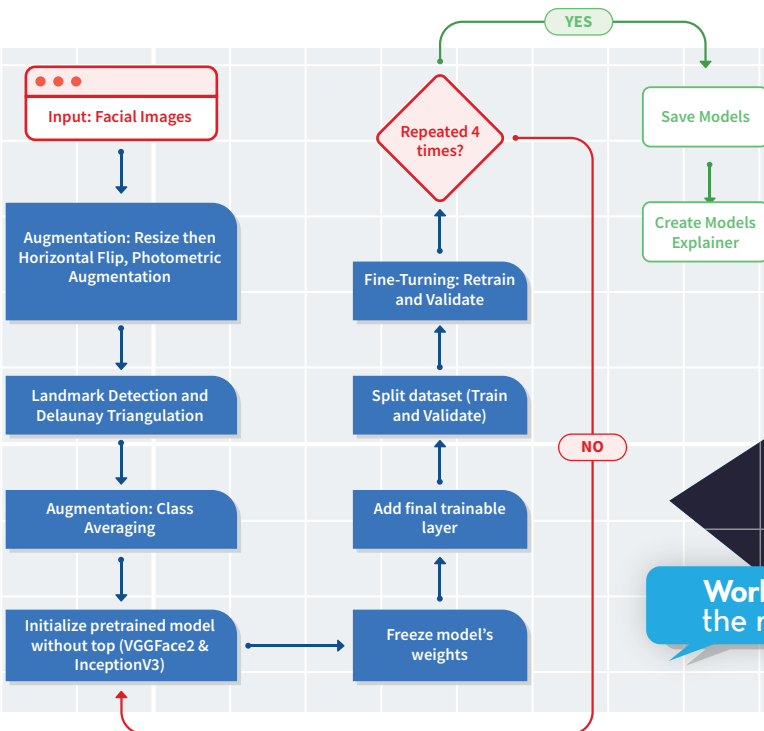
▼ Composite facial images retrieved from
Bangor University's Ward and Scott (2018).

RESEARCH METHODOLOGY

This research involves 3 main components, (i) augmentation of facial images dataset to create a more diverse dataset, (ii) creating models that are able to detect mental health disorder through facial features recognition which has comparable accuracy in comparison to previous researches and (iii) analyzing facial features that may explain the result of the prediction. CNN paradigm will be used in the creation of the machine learning models. Transfer learning will be used on the CNN models, employing VGGFace and resnet18 pretrained

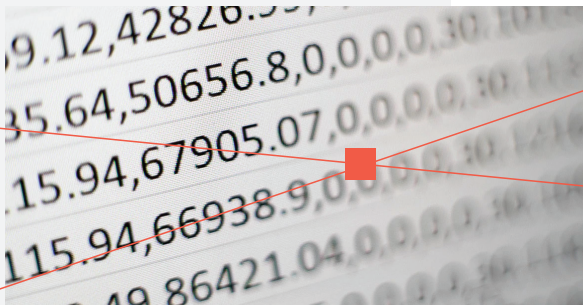
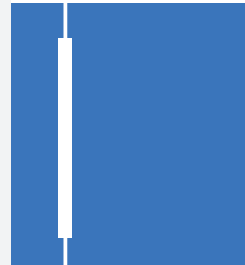
models. Explanation in the form of potential indicative features used in the models' decision will utilize LIME library. Finally, the experiment will compare attempts to rationalize the results of the models.

The following diagram shows the general workflow of the research. Both VGGFace2 and InceptionV3 based architecture will undergo the same workflow, the difference would lie in the initialization process/transfer learning process.



Workflow of the research

With the initial 54 images in the dataset, 4 augmentation methods (resizing, flipping, photometric adjusting, and averaging) were done. The models will then be initialized based on the pretrained models. The top part of the models refer to the end part of the architecture which serves as the classifier, which are the average pooling and the FCL part of the models. In the process of transfer learning, the non-top part of the model will be frozen, meaning that the weights are not altered during the training process. Through this weights freezing process, it is hoped that the learnt process done by the pretrained models in its previous task would be maintained. Next, the models will be trained over a 1:3 split dataset with k-fold validation scheme as a fine-tuning process. During fine-tuning, the classifier part of the model is trainable and hence would perform the desired task. Finally, the models that perform the best in each group will be explained using the LIME explainer.





+

■ RESULTS AND DISCUSSION

The augmentation module of this experiment resulted in the creation of a dataset with 336 images. Furthermore, 48 models trained with K-fold validation scheme were produced (24 VGGFace2 models, 24 InceptionV3 models). The average performance in each epoch is taken to visualize the overall performance of the models in regards to the parameters tested.

● ADAM VS. SGD

To assess the learning process as well the models' implementation, it is observed that the all the models begins predicting at 0.5 rate according to the probability of binary classification. When comparing the results produced by the 2 different models when using the different optimizers, we observe the earlier

convergence and overall performance of Adam in VGGFace pretrained model while the learning process tends to stagnate with the combination of SGD and VGGFace across all trials. Interestingly, the opposite occurs when using pretrained model InceptionV3, where SGD forms smoother learning curve as opposed to Adam. Using Adam optimizer in both models however, shows erratic learning curves. This is consistent with the foundation of Adam to adjust learning rates adaptively as opposed to the decay implemented using SGD. The stagnation of SGD in VGGFace2 models indicates that the optimizer is tucked in a local minima. It is also further implied by the convergence of the validation loss in each training instance approaching the training loss, and accuracy wobbling up and down with no significant changes.

As expected from the initial hypothesis regarding epochs, the numbers of epochs seemed to show signs of convergence in around 20-40 epochs although fluctuations were observed. There were points of huge fluctuations in different points at the training and validation process. This is due to the model weights change that could try to go to different directions at some points during the training process when it senses slowing down or worsening the learning process, especially for Adam optimizer. Although Adam contributes to the improvements of both models, SGD still showed the best performance in InceptionV3 models.

INCEPTION VS. VGGFACE2

As opposed to the initial hypothesis, the InceptionV3 model significantly performs better in comparison to custom VGGFace2 models although InceptionV3 is trained over classes of not only faces but other objects. It is also observed that InceptionV3 custom models converge faster in comparison to VGGFace2. Through the graphs, it is observed that the InceptionV3 model performs a better task in the detection throughout the k values in k-fold validation regardless of the optimizer used compared to VGGface2. Two things could be inferred from this phenomenon : (i) InceptionV3 architecturally performs better than

VGGFace2, and (ii) The optimizer used is dependent on the pretrained model.

Three reasonings came to be hypothesized when faced with the results. InceptionV3 input layers are larger dimensions than VGGFace2's input layer, this results in a larger number of information that the model could infer the predictions from. Another factor that may lead to better performance is the layers of InceptionV3 that emphasizes the features efficiently and accommodates higher dimension features. These 2 reasons are plausible explanations to the reflected results. On the other hand, VGGFace2 is trained in the attempt to capture features that identifies celebrities faces and is logically more adept in capturing the features of faces. In face identification, specific features might be omitted in the process in order to maintain the identity of the individuals. VGGFace2 does just this, its layers might dampen the features that reveal expressions and focus on identity identifying features.

Hence, the result obtained by the more general InceptionV3 is better than VGGFace2. It is important however, to consider that the performance ups and downs could be attributed to the identification of the identity that is present in both the training and testing data although uncertainty regarding that hypothesis could not be made sure upon

as theoretically different pixel values are present. The excellence in validation metrics of InceptionV3 model brings forth another question of whether the model predicts the output by identification as opposed to the facial features that reflect mental disorder. A counter argument could be built upon this case, where VGGFace should perform the task just as good if such an instance occurs when the results show that it doesn't.

The following tables summarizes the best model performances in each epoch of each varying parameters, in which we observe that InceptionV3 models on average dominate the performance across epochs.

Results – Models Performances (20 epochs)

Model	Avg Train Err	Avg Train Acc	Avg Val Err	Avg Val Acc
VGG Face - Adam	2.730309	0.623223	4.383151	0.57068
VGG Face - SGD	5.218674	0.499019	5.000868	0.5119
Inception V3 - Adam	0.231815	0.914238	2.888373	0.679761
Inception V3 SGD	0.606104	0.83755	1.999188	0.811014

Results – Models Performances (30 epochs)

Model	Avg Train Err	Avg Train Acc	Avg Val Err	Avg Val Acc
VGG Face - Adam	0.574392	0.80255	2.533499	0.641072
VGG Face - SGD	5.020149	0.512419	5.323728	0.520034
Inception V3 - Adam	0.180728	0.934591	2.063422	0.769739
Inception V3 SGD	0.952814	0.873478	2.180691	0.833141

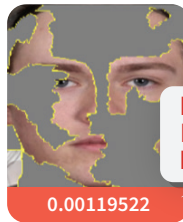
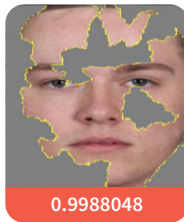
Results – Models Performances (30 epochs)

Model	Avg Train Err	Avg Train Acc	Avg Val Err	Avg Val Acc
VGG Face - Adam	0.35	0.87	2.77	0.65
VGG Face - SGD	6.59	0.51	6.77	0.48
Inception V3 - Adam	0.16	0.94	1.83	0.78
Inception V3 SGD	0.12	0.95	0.33	0.94

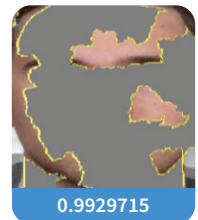
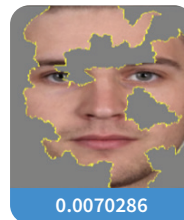
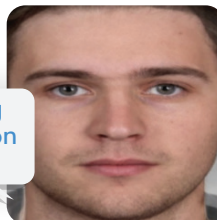
EXPLAINING THE AI MODEL RESULTS

The InceptionSGD4 model at 20 epochs has the best average validation accuracy of 0.977385 and VGGFaceAdam1 model at 40 epochs has the best accuracy of 0.66 in their respective pretrained model category. These models were used in the LIME explainer to investigate the observed facial features in creating the

decisions. The models will be referred to as their respective pretrained model name from now on. When explaining the results using lime on the InceptionV3 model that produces the best results, images MSH2 and MSL8 were used as test data, taken randomly.



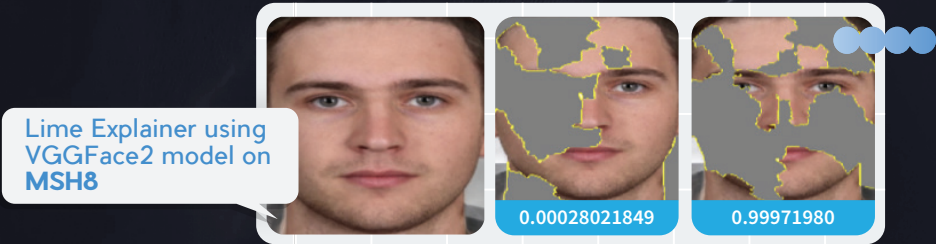
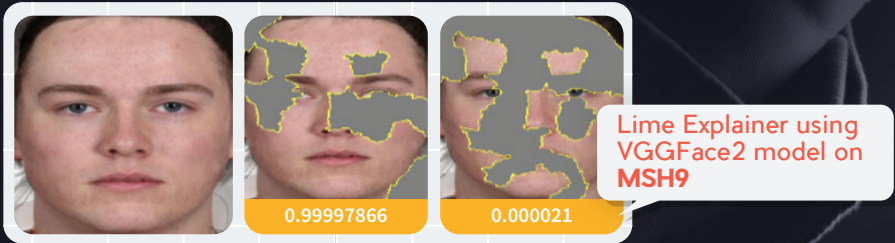
Lime Explainer using InceptionV3 model on MSH2



Lime Explainer using InceptionV3 model on MSL8

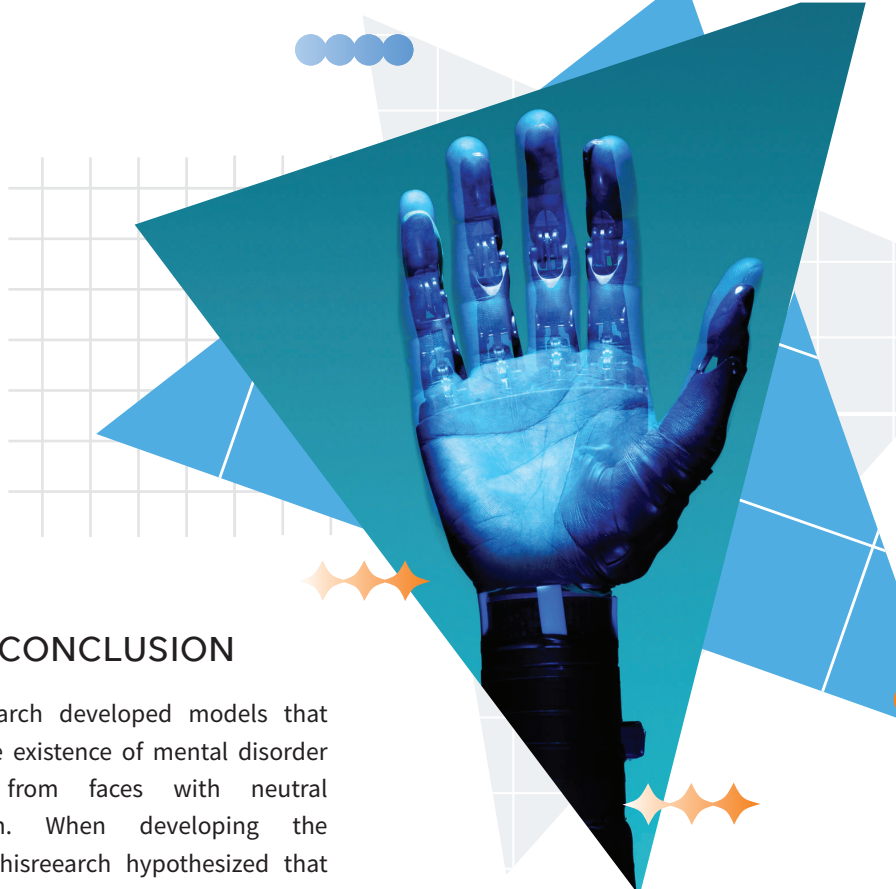
We see in the left side of the figure the image of subject MSH2 with schizophrenic tendencies and subject MSL8 on the right with normal mental health. The model successfully predicted the labels of the images, and the 2 images in each of the subject faces showed the level of confidence and the searched superpixels in the images. InceptionV3 classified MSH2 as H with probability of 0.998 and searches the superpixels around the center of the faces. This is also consistent in the H label prediction on MSL8 with probability of 0.007 in which

the model also searches around the area of the mouth, the eyes and and nose. Similarly, we observe that the L predictions on MSH2 with probability of 0.001 searches the otter sides of the faces, consistent with the search on MSL8 with L probability of 0.99. Moreover, we see that MSL8 L label detection also searches in areas where H does not search in both samples, the area of the forehead. This implies the superpixels used in judging the explanation made by the explainer. The search area is consistent throughout the labelling.



Interestingly, VGGFace2 showed similar regions of interest although the areas coverage are larger and more splattered in comparison to the explainer produced by InceptionV3 tests. Using the sample images, VGGFace2 correctly classified the images. Similar to the explanation made by InceptionV3, VGGFace2 searches the

outer region of the faces, while considering the center part of the face when predicting for H label; specifically, the area of the mouth, the eyes and and nose. This explanation is consistent with the experiment done by Ward and Scott (2018).



CONCLUSION

This research developed models that detect the existence of mental disorder features from faces with neutral expression. When developing the models, this research hypothesized that VGGFace2 pretrained model would perform better due to the similarity between the initial task of the pretrained model and the model developed in this experiment. However, results show that InceptionV3 models that are trained over varying classes actually outperformed VGGFace2 models that have been developed for the task of mental disorder detection.

The augmentation process of the dataset improves the performance of the models by allowing similar features to be trained on, or similar features to appear in the validation process. As for the optimizers,

Adam showed quicker convergence, quicker training time, and better performance in comparison to SGD as hypothesized from the mathematical standpoints of being faced with huge numbers of parameters in deep learning. Although, the difference in performance diminishes as the architecture of InceptionV3 outperformed VGGFace2 model in this experiment using both SGD and Adam optimizer. When implementing transfer learning with limited dataset, the numbers of epochs are known to be kept lower to prevent over-fitting.



The models produced reveal that the best average performance displayed by InceptionV3 model occurs at 20 epochs with accuracy of 0.977385 while VGGFace2 model displayed best performance at 40 epochs with accuracy of 0.66. Using the LIME explainer library, this research proved that the explainer provides an explanation that is still unclear on image data as interpretations of the explanation could be ambiguous although it shed mathematically logical explanation on the features that supports or oppose the predictions made. However, both best models take focus on the center part of the faces to predict for high tendency of mental disorder and outer regions to predict for low tendency of mental disorder.

◎ FUTURE WORKS

In this research, despite the evaluation metrics, one of the most challenging parts of the experiment is the scarcity of data. Future works might involve the evaluation of a more varying dataset to

ensure the convergence of weights towards mental disorder detection as opposed to identification of the faces itself. Moreover, the generalization of the mental disorders' physical manifestation leaves room for improvements such that a model that will be able to classify the mental disorder would be developed as opposed to merely detecting it in general.

To ensure that the models do not classify based on identification, the abandonment of the k-fold validation scheme could be done. Dataset splitting would be done by splitting the images based on the identity of the subjects, for example take 0.75 of the identities as training and another 0.25 as validation data from each category as opposed to randomly split the dataset using K-fold validation method. Additionally, explorations on different pretrained models to be used as well as alterations of different hyperparameters could be done to further increase confidence in the model produced.

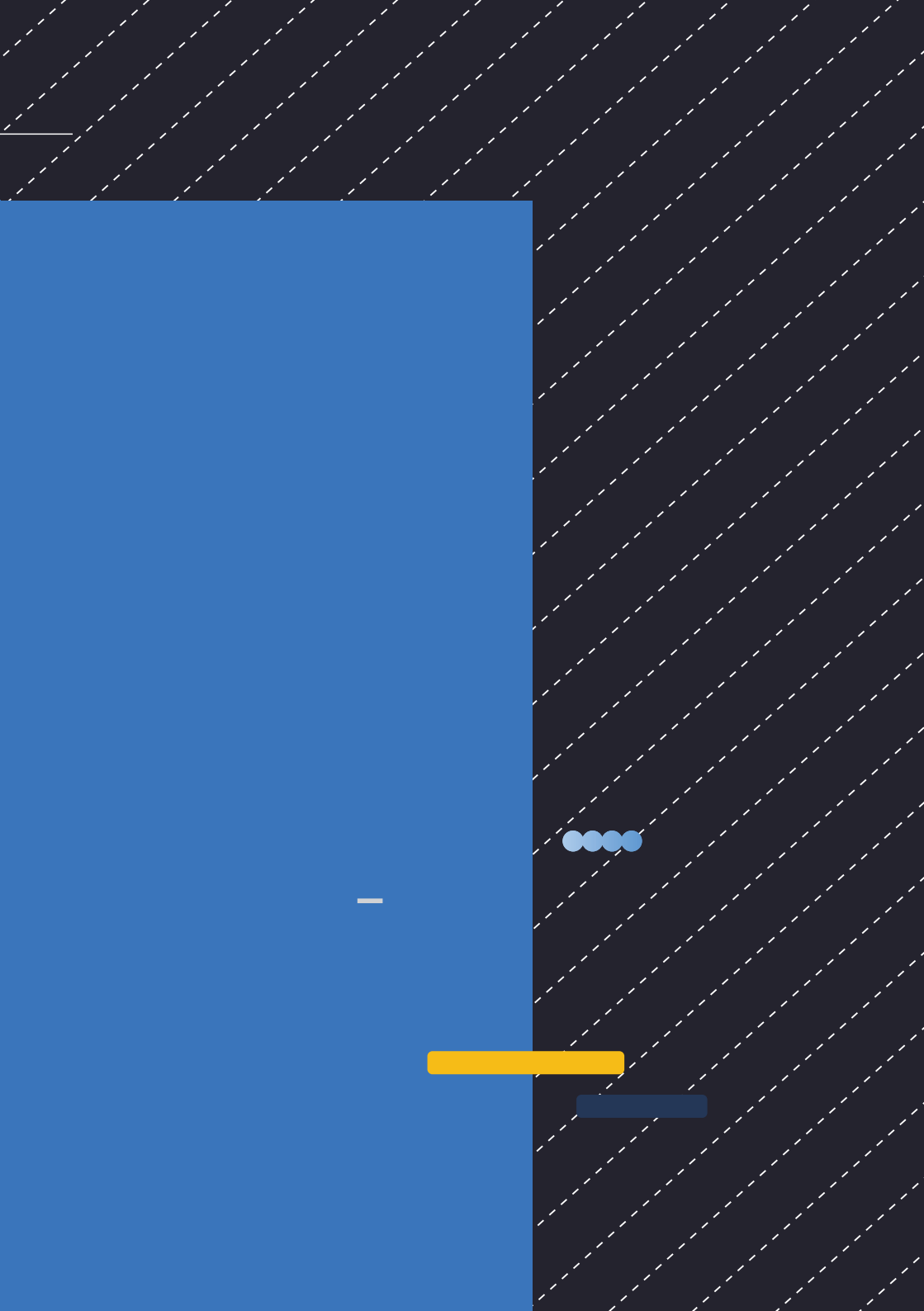


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ABOUT CFDS

Center for Digital Society (CfDS) is the research center established by the Faculty of Social and Political Sciences, Universitas Gadjah Mada. The institution is created under the concern over the contemporary dynamics of socio-political condition of the world that is accentuated by the impeccable influence of information technology. The phenomenon triggers the new patterns and complexities in the society, and thus requires new approaches in managing such complexities.

CfDS pledged to delve more on the study of contemporary digital society, including related issues surrounding the topic; such as the issues of smart city and urban development. The emphasis is then put on the utilization of technology to shape the society in becoming digitalized, as well as to bring solvency to social issues.

Vision

Solving Social Problem and Accelerating Prosperity through Indonesia Digital Society

Activities

1. Research and Development
2. Dissemination and Publication
3. Education and Policy Advocacy

Research Scopes

1. Digital Governance
2. Digital Economy
3. Future Technology



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