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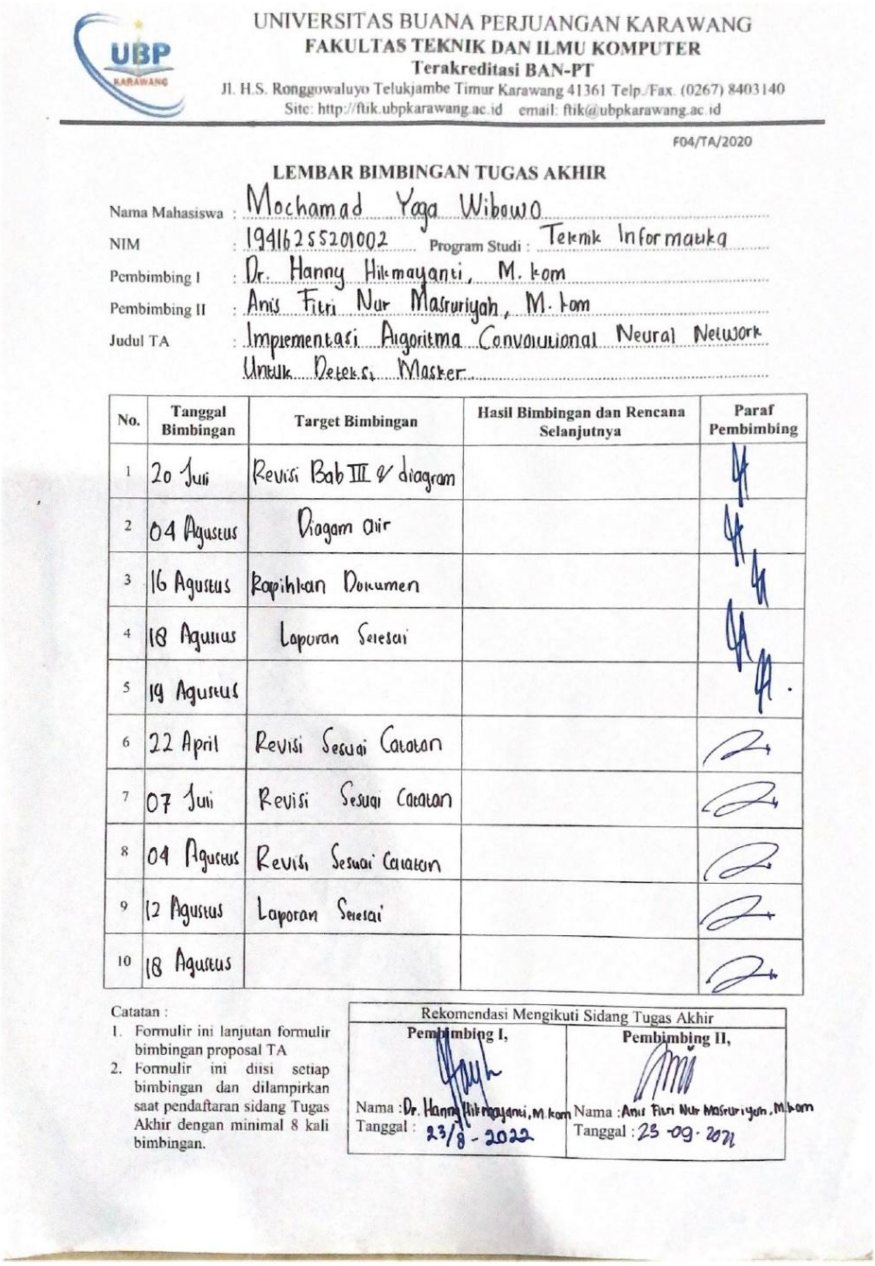
LAMPIRAN

Lampiran 1 Formulir Bimbingan Tugas Akhir



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Pembimbing II : Anis Fitri Nur Masruriyah, M. kom
Judul TA : Implementasi Algoritma Convolutional Neural Network Untuk Deteksi Masker

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Nama : Dr. Hanny Hikmayanti, M.kom	Nama : Anis Fitri Nur Masruriyah, M.kom
Tanggal : 23/8 - 2022	Tanggal : 23 - 09 - 2022

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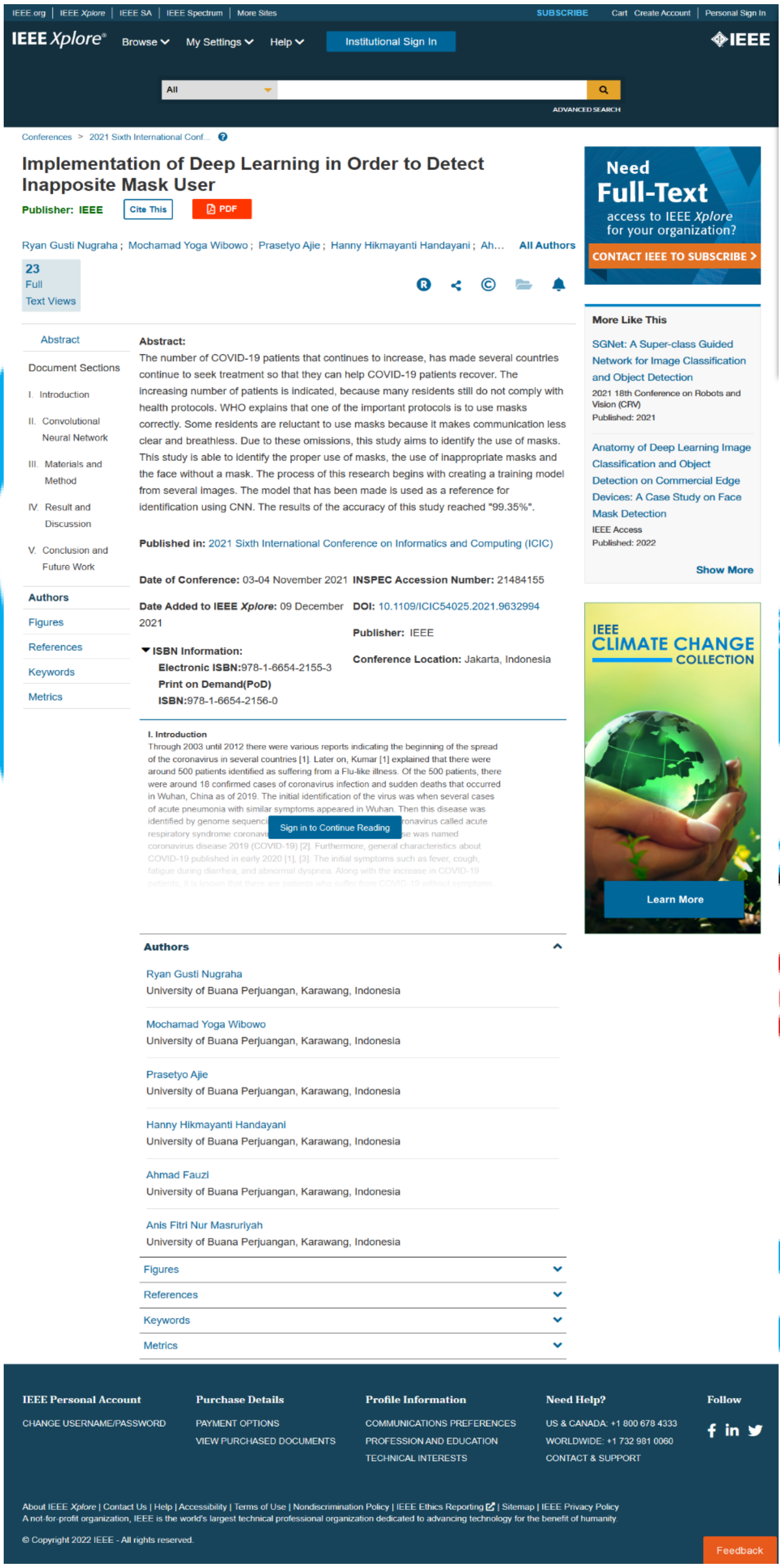

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Implementation of Deep Learning in Order to Detect Inapposite Mask User

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Abstract
Document Sections
I. Introduction
II. Convolutional Neural Network
III. Materials and Method
IV. Result and Discussion
V. Conclusion and Future Work
Authors
Figures
References
Keywords
Metrics

Abstract:
The number of COVID-19 patients that continues to increase, has made several countries continue to seek treatment so that they can help COVID-19 patients recover. The increasing number of patients is indicated, because many residents still do not comply with health protocols. WHO explains that one of the important protocols is to use masks correctly. Some residents are reluctant to use masks because it makes communication less clear and breathless. Due to these omissions, this study aims to identify the use of masks. This study is able to identify the proper use of masks, the use of inappropriate masks and the face without a mask. The process of this research begins with creating a training model from several images. The model that has been made is used as a reference for identification using CNN. The results of the accuracy of this study reached "99.35%".

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I. Introduction

Through 2003 until 2012 there were various reports indicating the beginning of the spread of the coronavirus in several countries [1]. Later on, Kumar [1] explained that there were around 500 patients identified as suffering from a Flu-like illness. Of the 500 patients, there were around 18 confirmed cases of coronavirus infection and sudden deaths that occurred in Wuhan, China as of 2019. The initial identification of the virus was when several cases of acute pneumonia with similar symptoms appeared in Wuhan. Then this disease was identified by genome sequenci Sign in to Continue Reading ronavirus called acute respiratory syndrome coronavi se was named coronavirus disease 2019 (COVID-19) [2]. Furthermore, general characteristics about COVID-19 published in early 2020 [1], [3]. The initial symptoms such as fever, cough, fatigue during diarrhea, and abnormal dyspnea. Along with the increase in COVID-19 patients, it is known that there are patients who suffer from COVID-19 without symptoms.

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Figures
References
Keywords
Metrics

Lampiran 3 Artikel Ilmiah

Implementation of Deep Learning in Order to Detect Inapposite Mask User

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***Abstract*— The number of COVID-19 patients that continues to increase has made several countries continue to seek treatment so that they can help COVID-19 patients recover. The increasing number of patients is indicated because many residents still do not comply with health protocols. WHO explains that one of the important protocols is to use masks correctly. Some residents are reluctant to use masks because it makes communication less clear and breathless. Due to these omissions, this study aims to identify the use of masks. This study is able to identify the proper use of masks, the use of inappropriate masks and the face without a mask. The process of this research begins with creating a training model from several images. The model that has been made is used as a reference for identification using CNN. The results of the accuracy of this study reached 0.9935%.**

Keywords—Convolutional Neural Network, COVID-19, Mask Detection, Identification, Image Processing

I. Introduction

Through 2003 until 2012 there were various reports indicating the beginning of the spread of the coronavirus in several countries [1]. Later on, Kumar [1] explained that there were around 500 patients identified as suffering from a Flu-like illness. Of the 500 patients, there were around 18 confirmed cases of coronavirus infection and sudden deaths that occurred in Wuhan, China as of 2019. The initial identification of the virus was when several cases of acute pneumonia with similar symptoms appeared in Wuhan. Then this disease was identified by genome sequencing technology as a new form of coronavirus called acute respiratory syndrome coronavirus 2 (SARS-CoV-2) and the disease was named coronavirus disease 2019 (COVID-19) [2]. Furthermore, general characteristics about COVID-19 published in early 2020 [1], [3]. The initial symptoms such as fever, cough, fatigue during diarrhea, and abnormal dyspnea. Along with the increase in COVID-19 patients, it is known that there are patients who suffer from COVID-19 without symptoms. Patients with asymptomatic COVID-19 in most cases deny their infection status or doubt the validity of the test.

The impact of denial of infection status is the transmission of COVID-19 which is difficult to identify because there are no symptoms and tests must be carried out to confirm. [2]. Hereinafter Khan [4], in his research explained the fact that COVID-19 can infect animals. The COVID-19 outbreak has caused several countries to suffer in various aspects, especially health, social and economic [5]. Indonesia was also frightfully affected by COVID-19 where the death rate increased to 8.9% at the end of March 2020 [6]. The Indonesian government provided policies related to controlling and overcoming the COVID-19 outbreak [7]. One of the policies made was Large-Scale Social Restrictions (LSSR) and residents who have high mobility carry out regular COVID-19 tests. This is expected to reduce the spread of the virus in Indonesia. [8]. On the other side, until the vaccine for COVID-19 has distributed and the main functions of the community were reopened, the number of patients infected with COVID has not decreased [9]–[11]. The increase in the number of infected with COVID-19 occurred due to there were still many residents who ignore health protocols [12]–[15].

The World Health Organization (WHO) explained that health protocols were one way to prevent and control COVID-19 [16]. Several health protocols are wearing masks, washing hands with soap and streaming water, maintaining distance, staying away from mobs, and limiting mobilization and interaction. Several studies have proven that the enactment of health protocols is able to help control the transmission of COVID-19 [17]–[19]. The main problem of compliance with health protocols is the inappropriate use of masks. Masks serve to minimize the transmission of COVID-19 through the air [20], [21]. Research conducted by [22], [23] proved that masks were able to reduce the transmission of COVID-19 in open areas. However, since there were still many residents who ignore the appropriate use of masks, many studies have carried out mask detection in open spaces [24]–[27].

Loey *et al.* [24] identified masks at the location of public facilities. The data employed in this study were 10,000 face images with masks and without masks. Furthermore, the image was processed by deep transferring learning as feature extraction and followed by classical machine learning methods. The results of this study indicate that the accuracy reaches 98% and successfully detects residents with masks and without masks. Afterward, Nagrath *et al.* [25] also identified masks using realtime data and Deep Neural Network (DNN) algorithms. The study applied more than 2,000 facial images as training data. Then tested using realtime data. The identification process begins with cleaning the data, then adjusting the image size in the pre-processing stage. . After the data is ready, the next step is to apply the

DNN to create an identification model. Based on the model built, the accuracy of the identification of the use of masks reaches 93% and is able to discipline residents to use masks.

Hereinafter, a study on mask detection using RetinaFaceMask was proposed by [26]. RetinaFaceMask was a simple stages detector consisting of a feature pyramid network to combine high-level semantic information with multiple feature maps and a new context attention module focused on detecting face masks. The study used 34,806 images with masks and without masks. Then the data was processed using RetinaFaceMask and proven to be able to detect faces with masks and without masks. The research accuracy rate reached 95.7%. Furthermore, Chowdary *et al.* [27] developed a transfer learning model to automate the process of identifying people who do not wear masks. Models are built by aligning pre-trained deep learning models. This model was a Simulated Masked Face Dataset (SMFD) which was able to overcome the limitations of data availability for better training and model testing. This model was proofed to outperform other recently proposed approaches by achieving 99.9% accuracy during training and 100% during testing.

Based on the research that has been described, all detect masks, yet none have detected the use of appropriate masks in detail. Some mask users only focus on covering their mouths, however, their noses were still seen. So that this study detected the correct use of masks. The rest of the study is structured as follows. Section 2 describes the Convolutional Neural Network, followed by sections. 3 with the application of a Convolutional Neural Network for mask detection. Section 4 shows the experimental results. Lastly, conclusions are given in Sections. 5.

II. Convolutional Neural Network

The term Deep Learning or Deep Neural Network refers to an artificial neural network with multiple layers. This network has been considered as one of the most powerful and popular in the literature due to its capability of handling large amounts of data. One of the most popular artificial neural networks is the Convolutional Neural Network (CNN). CNN method is taken from the name of the mathematical linear operation between a matrix which is often called convolution. Convolutional Neural Network has many layers including convolutional layer, non-linearity layer, pooling layer, and fully-connected layer. CNN has an excellent performance in machine learning problems, especially those related to image data, such as the largest image classification data set [28]. As previously addressed, this CNN focus on the basis that the input consists of images.

The focus on the architecture also was set in a way that best suits the need to handle certain types of data. One of the main differences is that the neurons are layered inside the CNN. Consists of neurons arranged into three dimensions, namely the input spatial dimensions (height, width, and depth). In practice, the input 'volume' will have dimensions of $64 \times 64 \times 3$ (height, width, and depth) leading to the final output layer. Furthermore, the final output consisting of dimensions $1 \times 1 \times n$ (where n represents the number of possible classes) input dimensions will be fully incorporated into the smaller volume of class scores [29]. In 1959 David Hubel and Torsten Wiesel conducted an experiment and described the neurons in the mammal's brain arranged in layers [30]. This layer learns how to recognize visual patterns starting with extracting local features and then combining the extracted features for higher level representation. This concept is also one of the core principles of Deep Learning. Artificial neural networks are self-regulating and are able to recognize visual patterns hierarchically through multiple learnings. In CNN there is also the term Neocognitron which became the first convolution idea proposed by Kunihiko Fukushima in 1980. Then it was matured by Yan LeChun in 1989 into a more modern convolution using a layered, unsupervised competitive learning algorithm [31], [32].

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Linear classification is also supervised with training carried out separately for the output layer. In 2012 Alex Krizhevsky developed the ImageNet Large Scale Visual Recognition Challenge which uses a CNN model called AlexNet with a GPU used to train AlexNet. K. Grm [33] explained that in a systematic study there are strengths and weaknesses of the model, specifically such as image quality, blur, JPEG compression, occlusion, noise, image brightness, contrast, missing pixels, and model characteristics. However, AlexNet is able to accommodate these weaknesses. In this mask detection research, there are two main processes, namely the first to train or train the mask detector and the second to apply or apply the mask detector using AlexNet. Figure 1 is a process to create the model training.

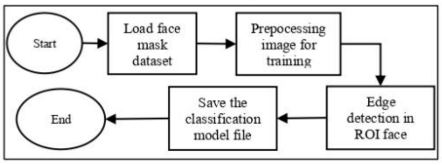

Figure 1 Phase of Training Model

Furthermore, Figure 2 is the stage for detecting the use of masks as recommended. The detection process uses real time images.

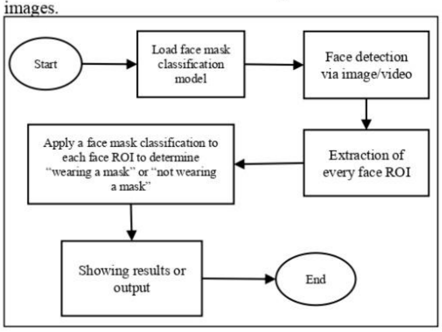

Figure 2 Implementation of Face Mask Detector

III. Materials and Method

A. Materials

This study drew upon image data with Portable Network Graphic (PNG) format which is used as material for making models. The total image used is 3863 and is divided into 1930 images with faces using masks. Then, another image is a face without using a mask. Furthermore, at the testing stage, the image used is in the form of live video captured using a camera. Dataset for mask detection training needs by taking images from various sources on the internet and using the JPEG2000 image format. JPEG2000 format was chosen because it has been optimized from the JPEG version has a good compression ratio. The image dataset collected must have a balanced or equivalent composition between wearing a mask and not wearing a mask with the same person object. Figure 3 showed the sample of images.

Figure 3 Dataset Training

B. Preprocessing

After the data was obtained as needed, the next step was to do preprocessing. Preprocessing helps out to remove noise and parts that are not needed in the input image for further processing [34]. Preprocessing is able to improve data quality so that it significantly affects the model made. Various preprocessing techniques were created to make the data meet the model's input requirements, increase the relevance of the prediction targets and make the optimization step of the model easier. In this research, preprocessing was done by adjusting the image size, filtering, and object labeling. Detail of the dataset is shown in Table I.

TABLE I. DETAIL DATASET

Label	Description	Total
Mask	Face with mask	1924
Non-Mask	Face without mask	1933

Algorithm 1 is the stages for the training model at the data preprocessing stage.

Algorithm I Preprocess of Training Model

Input : image dataset
Output : Model
Algorithm

1 Load image dataset
2 Create a container array for the dataset
3 Process images such as, resizing, cropping, and inserting into an array
4 Perform data augmentation, and share data for training and testing
5 Load the MobilenetV2 model from Keras. do training and compile using Adam optimizer
6 Create and save the model file.

C. Segmentation

The segmentation process aims to separate the object (foreground) from the background [35] [36].. Segmentation also has the nature of experimental, subjective, and depends on the goals to be achieved. In this research, the segmentation method used is edge detection. Edge detection serves to identify the boundary of an object contained in the image.

Restrictions in this study lay in the face, eyes, nose, and mouth. The result of implementing edge detection is shown in Figure 4. A green line appears on the displayed face. The line is the confine that has been set to identify the proper use of masks or not. Other than that limit, it is not be going to take into account.

Figure 4 Image Segmentation

D. Feature Extraction

After the segmentation stage is equipped, the next process is to perform feature extraction. Feature extraction is able to handle significant feature areas in the image depending on the intrinsic characteristics and the application. In this study, feature extraction employed OpenCV DNN where this model is based on the 'Single Shot Multi-box Detector' (SSD) and applied the 'ResNet-10' architecture as the base model. SSD is known to have almost the same stages as the YOLO technique. Where to take only one capture to detect more than one object in the image using Multibox.

Furthermore, Caffemodel is implemented on the SSDMNV2 model to detect faces and then detect the presence of face masks. Caffe is a deep learning framework that was developed to be faster, more powerful, and efficient than other object detection methods. Caffe is created and managed by Berkeley AI Research (BAIR) and the community. After applying the face detection model, the system gets the number of faces detected, then the location for the bounding boxes, and the confidence score for the prediction.

The output of this process is then used as input for classifying face mask detectors. By using this approach allows real-time face detection without using a lot of resources. Moreover, it can also detect faces in different orientations with good accuracy.

E. Implementation of CNN

The CNN process in this study embarked after reading the image. Then the image was processed on feature maps consisting of convolution and pooling techniques. Convolution is an efficient method of feature extraction and is skilled in reducing data dimensions. Each kernel serves as a feature identifier, filtering out where that feature is in the original image [37] [38]. Furthermore, the pooling technique was carried out to reduce the dimensions of the feature maps. So that it was able to speed up computation because fewer parameters need to be updated and it capable overcome overfitting. The feature maps process was repeated until all images were processed. Hereafter, the resulting feature maps were still in the form of a multidimensional array with the result that a reshape feature (flatten layer) was carried out to get the vector value. The vector value that had been obtained was used as input from the fully connected layer. In the fully connected layer, there were hidden layers, activation functions, output layers, and loss functions. An illustration of how CNN works is shown in Figure 5.

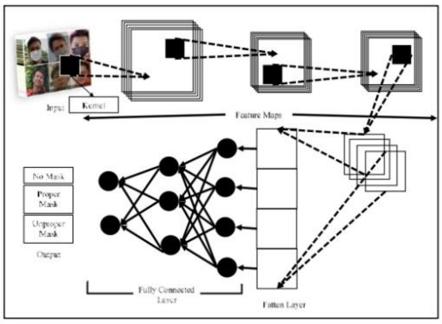

Figure 5 CNN Stages

IV. Result and Discussion

The results of the preprocessing carried out in this study were changing the color space from BGR to RGB, then resizing the image to 224x224. Furthermore, segmentation was done to determine the threshold of the face. The results of segmentation Feature extraction was done by distinguishing the texture of the image used as a model and direct video capture using the camera.

In the training phase, CNN trained 1924 images wearing masks and 1933 images without masks. Furthermore, in the training section, the system uses the learning rate 10^{-4}because if the learning rate exceeds10^{-4}, overheating was able to occur. While the learning rate function is to increase the effectiveness of the learning rate parameters. On the other hand, the learning rate is a parameter that serves to increase the learning speed of back propagation as a training function.

The evolutionary training architecture was trained for 20 epochs (iterations) and the batch size was 32. Batch size was the number of data samples that was going to be distributed to neural networks. Figure 6 showed the accuracy results after training, both loss and accuracy. The accuracy of a very good system where the training loss is very small, close to 0 (zero). In testing the face mask detection system, the accuracy value is 0.9935% with a training loss of 0.0309%. Furthermore, the existing image was going to be identified as the face. If a face was detected on the camera, a bounding box was displayed and a description was included above the bounding box.

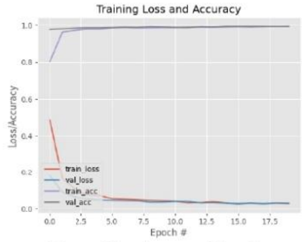

Figure 6 the Accuracy Results

In Figure 7, the bounding box designated the face, and then the bounding box labeled the object. The object in the camera capture was detected as a face and did not use a mask, so the bounding box was red. Furthermore, in Figure 8-A it emerged that the object wore a mask, however, the marking of the bounding box was still red. This is since the object applied the mask inapposite with the provisions. The mask functions to cover the nose and mouth, yet the object that wore the mask in Figure 8-A was not used properly. This also occurred in the object in Figure 8-B. It came into view that the object had used a mask, but had not smothered completely. The nose was still to be seen, so it was categorized as not wearing a mask properly.

Figure 7 Identification without Mask

A B

Figure 8 Identification using Unproper Mask

On the other hand, if the mask was employed correctly, the color of the bounding turned green with the caption "memakai masker". Figure 9 was the result of identifying the correct usage of masks. This allowed for the utilization of surveillance cameras in the open areas. So that supervisors were able to give warnings to visitors or residents who wear masks improperly.

Figure 9 Identification Proper Mask

Furthermore, by using the decision tree algorithm and support vector machine, the accuracy obtained is shown in Table II.

TABLE II. ACCURACY COMPARISON

Algorithm	Accuracy (%)
Decision Tree	92.22
Support Vectore Machine	98.50
Artificial Neural Network	99.00
Convolutional Neural Network	99.35

V. Conclusion and Future Work

This study utilizes facial object data with and without masks also proves that CNN was able to identify the use of masks excellently. This was evidenced by the accuracy value that reaches 99.35% and is the best among other algorithms that have been tried. Wearing masks correctly capable to protect people from the spread of COVID-19. Some things that must be considered in wearing a mask are to cover the nose and mouth to the maximum. It is known that droplets are able to go in through the nose and mouth when communicating directly.

Moreover, for further research, it is better to use alarm technology to warn residents to alert them properly. If the camera captures a visitor who is not wearing a mask properly, the alarm will ring. Furthermore, giving notice that there are visitors who wear masks recklessly.

Acknowledgment

We would like to thank the research and community service institutions and the Faculty of Engineering and Computer Science, Universitas Buana Perjuangan Karawang who have provided support and assistance for the implementation of this research.

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Lampiran 4 Coding Program

jupyter latih_masker.py Last Friday at 12:53 PM Logout

File Edit View Language Python

```python
# import library yg dibutuhkan
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.applications import MobileNetV2
from tensorflow.keras.layers import AveragePooling2D
from tensorflow.keras.layers import Dropout
from tensorflow.keras.layers import Flatten
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import Input
from tensorflow.keras.models import Model
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.applications.mobilenet_v2 import preprocess_input
from tensorflow.keras.preprocessing.image import img_to_array
from tensorflow.keras.preprocessing.image import load_img
from tensorflow.keras.utils import to_categorical
from sklearn.preprocessing import LabelBinarizer
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
from imutils import paths
import matplotlib.pyplot as plt
import numpy as np
import os

# menginisialisasi kecepatan pelatihan awal, jumlah periode,
# dan ukuran batchnya
INIT_LR = 1e-4
EPOCHS = 20
BS = 32

#folder berisi dataset
DIRECTORY = r"C:\UAS_PCD\dataset"
CATEGORIES = ["dengan_masker", "tanpa_masker"]

# mengambil list gambar yang ada di folder dataset, lalu menginisialisasi
# daftar data gambarnya
print("[INFO] loading dataset gambar...")

data = []
labels = []

for category in CATEGORIES:
    path = os.path.join(DIRECTORY, category)
    for img in os.listdir(path):
        img_path = os.path.join(path, img)
        image = load_img(img_path, target_size=(224, 224))
        image = img_to_array(image)
        image = preprocess_input(image)

        data.append(image)
        labels.append(category)

# melakukan one-hot encoding pada labels
lb = LabelBinarizer()
labels = lb.fit_transform(labels)
labels = to_categorical(labels)

data = np.array(data, dtype="float32")
labels = np.array(labels)

(trainX, testX, trainY, testY) = train_test_split(data, labels,
    test_size=0.20, stratify=labels, random_state=42)
```

jupyter latih_masker.py✓ Last Friday at 12:53 PM Logout

File Edit View Language Python

```python
labels = np.array(labels)

(trainX, testX, trainY, testY) = train_test_split(data, labels,
    test_size=0.20, stratify=labels, random_state=42)

# membuat generator gambar pelatihan untuk augmentasi data
aug = ImageDataGenerator(
    rotation_range=20,
    zoom_range=0.15,
    width_shift_range=0.2,
    height_shift_range=0.2,
    shear_range=0.15,
    horizontal_flip=True,
    fill_mode="nearest")

#CNN
baseModel = MobileNetV2(weights="imagenet", include_top=False,
    input_tensor=Input(shape=(224, 224, 3)))
headModel = baseModel.output
headModel = AveragePooling2D(pool_size=(7, 7))(headModel)
headModel = Flatten(name="flatten")(headModel)
headModel = Dense(128, activation="relu")(headModel)
headModel = Dropout(0.5)(headModel)
headModel = Dense(2, activation="softmax")(headModel)

model = Model(inputs=baseModel.input, outputs=headModel)

for layer in baseModel.layers:
    layer.trainable = False

# membuat file model
print("[INFO] mengcompile model...")
opt = Adam(lr=INIT_LR, decay=INIT_LR / EPOCHS)
model.compile(loss="binary_crossentropy", optimizer=opt,
    metrics=["accuracy"])

# melakukan training pada network
print("[INFO] melatih network pendeteksi masker...")
H = model.fit(
    aug.flow(trainX, trainY, batch_size=BS),
    steps_per_epoch=len(trainX) // BS,
    validation_data=(testX, testY),
    validation_steps=len(testX) // BS,
    epochs=EPOCHS)

# melakukan test prediksi dan evolusi
print("[INFO] mengevolusi network...")
predIdxs = model.predict(testX, batch_size=BS)

predIdxs = np.argmax(predIdxs, axis=1)

# membuat report hasil klasifikasi
print(classification_report(testY.argmax(axis=1), predIdxs,
    target_names=lb.classes_))

# menyimpan model ke dalam disk
print("[INFO] menyimpan model deteksi masker...")
model.save("deteksi_masker.model", save_format="h5")

# membuat plot dari loss, dan akurasi dari hasil pelatihan
```


```python
# melakukan test prediksi dan evolusi
print("[INFO] mengevolusi network...")
predIdxs = model.predict(testX, batch_size=BS)

predIdxs = np.argmax(predIdxs, axis=1)

# membuat report hasil klasifikasi
print(classification_report(testY.argmax(axis=1), predIdxs,
    target_names=lb.classes_))

# menyimpan model ke dalam disk
print("[INFO] menyimpan model deteksi masker...")
model.save("deteksi_masker.model", save_format="h5")

# membuat plot dari loss, dan akurasi dari hasil pelatihan
```


```python
N = EPOCHS
plt.style.use("ggplot")
plt.figure()
plt.plot(np.arange(0, N), H.history["loss"], label="train_loss")
plt.plot(np.arange(0, N), H.history["val_loss"], label="val_loss")
plt.plot(np.arange(0, N), H.history["accuracy"], label="train_acc")
plt.plot(np.arange(0, N), H.history["val_accuracy"], label="val_acc")
plt.title("Training Loss and Accuracy")
plt.xlabel("Epoch #")
plt.ylabel("Loss/Accuracy")
plt.legend(loc="lower left")
plt.savefig("plot.png")
```

jupyter deteksi_masker_video.py Yesterday at 10:54 AM Logout

File Edit View Language Python

```python
# import library yg dibutuhkan
from tensorflow.keras.applications.mobilenet_v2 import preprocess_input
from tensorflow.keras.preprocessing.image import img_to_array
from tensorflow.keras.models import load_model
from imutils.video import VideoStream
import numpy as np
import imutils
import time
import cv2
import os

def deteksi_prediksi_masker(frame, faceNet, maskNet):
    # mengambil dimensi dari framenya kemudian membuat blob nya
    (h, w) = frame.shape[:2]
    blob = cv2.dnn.blobFromImage(frame, 1.0, (224, 224),
        (104.0, 177.0, 123.0))

    faceNet.setInput(blob)
    detections = faceNet.forward()
    print(detections.shape)

    # membuat variabel array untuk menampung list daftar wajah, lokasi
    # dan daftar prediksi dari network deteksi masker
    faces = []
    locs = []
    preds = []

    # melakukan looping pada pendeteksian
    for i in range(0, detections.shape[2]):
        # mengekstrak nilai keyakinan (probabilitas) yang terkait
        #  dengan deteksi
        confidence = detections[0, 0, i, 2]

        # memfilter deteksi yang lemah dengan nilai keyakinan
        # lebih besar dari keyakinan yang minimum
        if confidence > 0.5:
            # menghitung koordinat (x,y) kotak pembatas untuk objek
            box = detections[0, 0, i, 3:7] * np.array([w, h, w, h])
            (startX, startY, endX, endY) = box.astype("int")

            # memastikan kotak pembatas berada di dalam dimensi frame
            (startX, startY) = (max(0, startX), max(0, startY))
            (endX, endY) = (min(w - 1, endX), min(h - 1, endY))
```

jupyter deteksi_masker_video.py Yesterday at 10:54 AM Logout

File Edit View Language Python

```python
            # memastikan kotak pembatas berada di dalam dimensi frame
            (startX, startY) = (max(0, startX), max(0, startY))
            (endX, endY) = (min(w - 1, endX), min(h - 1, endY))
```


```python

            # mengekstrak ROI wajah, konversikan dari BGR ke RGB
            # mengurutkan, mengubah ukurannya ke 224x224, dan memprosesnya
            face = frame[startY:endY, startX:endX]
            face = cv2.cvtColor(face, cv2.COLOR_BGR2RGB)
            face = cv2.resize(face, (224, 224))
            face = img_to_array(face)
            face = preprocess_input(face)

            # menambahkan wajah dan kotak pembatas ke list
            faces.append(face)
            locs.append((startX, startY, endX, endY))

    # hanya melakukan pendeteksian ketika setidaknya satu wajah terdeteksi
    if len(faces) > 0:
        faces = np.array(faces, dtype="float32")
        preds = maskNet.predict(faces, batch_size=32)

    # mengembalikan nilai dari lokasi wajah dan lokasi yang sesuai
    return (locs, preds)

# mengload serialized pendeteksi wajah model
prototxtPath = r"face_detector\deploy.prototxt"
weightsPath = r"face_detector\res10_300x300_ssd_iter_140000.caffemodel"
faceNet = cv2.dnn.readNet(prototxtPath, weightsPath)

# mengload model deteksi masker yang telah dibuat
maskNet = load_model("deteksi_masker.model")

# memulai service video webcam
print("[INFO] memulai stream webcam...")
vs = VideoStream(src=2).start()

# melooping setiap frame dari capture video webcam
while True:
    # mengambil tiap frame dari video dan merizenya
    # menjadi maximum lebar 400 pixels
    frame = vs.read()
    frame = imutils.resize(frame, width=720)

```

jupyter deteksi_masker_video.py Yesterday at 10:54 AM Logout

File Edit View Language Python

```python
# melooping setiap frame dari capture video webcam
while True:
    # mengambil tiap frame dari video dan merizenya
    # menjadi maximum lebar 400 pixels
    frame = vs.read()
    frame = imutils.resize(frame, width=720)

    # mendeteksi wajah dalam bingkai dan menentukan apakah
    # memakai masker atau tidak menggunakan function diatas
    (locs, preds) = deteksi_prediksi_masker(frame, faceNet, maskNet)

    # melooping di lokasi terdeteksi wajah dan lokasi
    # yang sesuai
    for (box, pred) in zip(locs, preds):
        # membuka kotak pembatas dan memprediksi
        (startX, startY, endX, endY) = box
        (mask, withoutMask) = pred

        # mententukan label dan warna yang akan digunakan
        # untuk menggambar kotak pembatas dan teks
        label = "Memakai Masker" if mask > withoutMask else "Tidak Memakai Masker"
        color = (0, 255, 0) if label == "Memakai Masker" else (0, 0, 255)

        # menyertakan nilai probabilitas di label
        label = "{}: {:.2f}%".format(label, max(mask, withoutMask) * 100)

        # menampilkan label dan kotak pembatas pada
        # video frame
        cv2.putText(frame, label, (startX, startY - 10),
            cv2.FONT_HERSHEY_SIMPLEX, 0.45, color, 2)
        cv2.rectangle(frame, (startX, startY), (endX, endY), color, 2)

    # menampilkan output dari video
    cv2.imshow("Pendeteksi Masker", frame)
    key = cv2.waitKey(1) & 0xFF

    # jika tombol 'q' ditekan, maka memberhentikan looping
    if key == ord("q"):
        break

# memberhentikan proses
cv2.destroyAllWindows()
vs.stop()
```

Lampiran 5 Lembar Perbaikan Sidang Tugas Akhir

UNIVERSITAS BUANA PERJUANGAN KARAWANG
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Terakreditasi BAN-PT
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Site: http://ftik.ubpkarawang.ac.id email: ftik@ubpkarawang.ac.id

LEMBAR PERBAIKAN KETUA PENGUJI
SIDANG TUGAS AKHIR

Nama Mahasiswa : Mochamad Yoga Wibowo
N I M : 19416255201002
Program Studi : Teknik Informatika
Judul Tugas Akhir : IMPLEMENTASI ALGORITMA CONVOLUTIONAL NEURAL NETWORK UNTUK DETEKSI MASKER

NO	PERBAIKAN	HALAMAN	PARAF
1	Cover dan lembar pengesahan sesuai dengan format terbaru	Cover, ii	
2	Penggunaan huruf italic untuk bahasa asing	ix, 8, 22, 23	

Karawang, ...
Ketua Penguji,

Tatang Rohana, M. Kom
NIDN : 0412047201

UNIVERSITAS BUANA PERJUANGAN KARAWANG
FAKULTAS TEKNIK DAN ILMU KOMPUTER
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Site: http://ftik.ubpkarawang.ac.id email: ftik@ubpkarawang.ac.id

LEMBAR PERBAIKAN PENGUJI 1
SIDANG TUGAS AKHIR

Nama Mahasiswa	:	Mochamad Yoga Wibowo
N I M	:	19416255201002
Program Studi	:	Teknik Informatika
Judul Tugas Akhir	:	IMPLEMENTASI ALGORITMA CONVOLUTIONAL NEURAL NETWORK UNTUK DETEKSI MASKER

NO	PERBAIKAN	HALAMAN	PARAF
1	Cover dan lembar pengesahan sesuai dengan format terbaru	Cover, ii	✓
2	Penggunaan huruf italic untuk bahasa asing	ix, 8, 22, 23	

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NO	PERBAIKAN	HALAMAN	PARAF
1	Cover dan lembar pengesahan sesuai dengan format terbaru	Cover, ii	
2	Penggunaan huruf italic untuk bahasa asing	ix, 8, 22, 23	

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