A Hybrid Machine Learning and Fuzzy Inference Approach with UAV for Indoor Virus Contamination Risk

Esra Çakır*, Furkan Erdi, Emre Demircioğlu, and Mehmet Ali Taş

***Abstract*—With the impact of the Covid-19 pandemic in 2020, major established health rituals were forced to transform. The most well-known of these is the medical mask, which is widely used and required to be worn in designated areas. Although pandemic regulations have been relaxed recently, health authorities agree that wearing masks, especially in closed areas, is a life-saving measure. Proper use of face masks is one of the most effective, easy and inexpensive actions to prevent the rapid spread of viruses indoors. By examining the use of masks in closed areas, the risk of transmission of the virus can be analyzed, and the measures can be determined correctly. Taking advantage of up-to-date technological equipment and approaches are important tools for making these determinations accurately and easily. In this study, the risk of indoor virus transmission from mask wearing styles is analyzed with an integrated method that includes Machine Learning (ML) and Fuzzy Inference System (FIS) approach. In order to achieve this, images taken from the camera of the Unmanned Aerial Vehicle (UAV), which is one of the current technologies suitable for contactless, mobile operations, were used. While determining the mask wearing status with the help of machine learning over the images, the ambient temperature and the mask wearing ratio gave the risk results with the fuzzy inference system. The results are intended to guide decision makers in identifying and implementing measures to reduce and prevent the spread of the virus indoors.**

***Index Terms*—Covid-19, fuzzy inference system; indoor locations, machine learning, mask detection, Python, risk analysis, UAV, virus contamination**

I. INTRODUCTION

Since the declaration of the pandemic, more than six and a half million people have died from diseases caused by the COVID-19 virus [1]. Thanks to increased vaccination and the improved immunity of survivors, daily death rates have been lower recently than when the pandemic peaked [2]. However, it is essential to be vigilant, as some diseases such as seasonal influenza and diseases caused by the Covid-19 virus show similar symptoms [3]. Moreover, variants of the virus that emerge over time continue to threaten public health [4, 5]. These reveal that medical face masks, one of the first and most successful measures applied in the pandemic, are shown to be a part of daily life for many years to come [6]. Although the high rate of wearing a mask is promising, wearing the mask properly is also an issue that should be noticed [7]. Compliance with the instructions for use recommended by the World Health Organization (WHO) is of vital importance in protecting the person and those around him from the spread of the virus [8]. It can be useful to monitor mask detection and the way they are worn indoors, which are environments that are conducive to the spread of the virus by nature [9]. Unmanned Aerial Vehicles (UAVs) (also called drones) are modern technological tools that can be used for contactless and mobile detection [10]. Photographing and temperature measurement, which are remarkable features offered by UAVs, can be used to obtain data for investigate environment. Thus, the data of unmanned aerial vehicles are suitable for analyzing the risk level.

In the literature, some studies have been implemented to monitor the use of masks and whether the person wears a mask analyzed with artificial neural networks, machine learning, deep learning, and so on. Loey *et al.* [11] used a two-component method that includes Resnet50 for feature extraction for face mask detection in public areas, and a Support Vector Machine (SVM), decision trees and ensemble algorithm for classification. Gupta *et al.* [12] proposed a machine learning face classification system to determine whether a person is wearing a mask. Msigwa *et al.* [13] also studied mask usage by applying traditional machine learning algorithms and Convolutional Neural Networks (CNNs) to thermal images. UAVs were frequently selected for images to be analyzed. The studies of Meivel *et al.* [10], Alinra *et al.* [14], Othman and Aydin [15] can be given as examples of studies in which the processed images are taken from UAVs to evaluate the data using neural networks, machine learning, deep learning, and so on.

This study proposes a contamination risk analysis for indoor using the mentioned features of the UAVs, the mask usage rates of the people are obtained by processing the images with machine learning. Fuzzy inference system is used to see the effect of ambient temperature on the risk of contamination. The data is reflected as fuzzy with ordinary membership degrees. Instead of final acceptance and rejection decisions, it has become easier to include transition values in the decision-making process. After Zadeh's presentation of fuzzy logic theory to the literature in 1965, elements can be defined by their membership in sets [16]. A fuzzy number's degree of membership represents its belonging to the set. On the other hand, Fuzzy Inference System (FIS) is the process of formulating a particular input-to-output mapping using fuzzy logic [17]. The matches provide a basis on which decisions can then be made or distinguishable patterns can be made [18]. The fuzzy inference system makes it possible to predict by using logical inferences in decision making applications. Infection risk assessment is made according to the rules written in the fuzzy inference system, mask usage information and ambient temperature. The authors of this paper have previously

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experienced a preliminary study as one-person experiments and obtained meaningful results [19]. The main expected contribution of the study is the processing of UAV image data with the help of machine learning and fuzzy inference system in multi-person environments. The proposed model is considered innovative in terms of fuzzy inference system designs and the development of new models to use data from UAV properties.

The paper is organized as follows. The materials, software and proposed hybrid method are presented in Section II. In addition, fuzzy inference system and fuzzy rules used in mask detection and indoor temperature-based contamination risk analysis are given in this section. The proposed approach is applied in Section III. More specifically, mask detection is performed by processing the images taken by the unmanned aerial vehicle with machine learning, and then the indoor risk evaluation results are revealed in the fuzzy inference system with mask wearing rate and temperature information. The results are detailed and discussed in Section IV. Finally, Section V includes the evaluation of the study and suggestions for future studies.

II. Materials and Methodology

This study consists of three main parts. The first is to obtain data with the help of drone features. Second, mask usage detection from UAV images with the developed machine learning algorithm. Finally, the proposed fuzzy inference system rules to determine the level of indoor contamination risk assessment. Information about the materials and models used for these three sections is given below.

A. *Data Acquisition by Unmanned Aerial Vehicle*

Unmanned Aerial Vehicles (UAVs) are well suited for quickly and effectively scan the environment in motion and without contact. In recent years, the use of UAVs has been included in applications in the health sector as well as being used in logistics, defense industry, image processing and environmental data collection.

In this study, DJI Tello Edu Drone was used to take images and measure the ambient temperature. Tello EDU is a programmable tool for training in Python environment. It supports Electronic Image Stabilization [20]. Video stream data can be accessed with Tello EDU, which creates the possibility for image processing and artificial intelligence development. SDK 2.0 [21] enables further development of Tello EDU by performing artificial intelligence functionality such as object recognition, tracking, programmatic 3D reconstruction, computer vision and deep learning technologies. In this study, "*djitellopy (version 2.4.0)*" module is used in order to program the drone in the python environment and access its features. The data measured by the temperature sensor also contributes to the determination of the indoor temperature.

B. *Mask Wearing Detection with Machine Learning in Python*

A new Python module has been prepared to detect the mask usage status of the people in the images. Some libraries used in the module include: Open Source Computer Image Library "*opencv_python (version 4.6.0.66)*" library is useful for image analysis, image processing, detection, recognition, etc. In this study, it is used to rotate the images taken by the UAV in a viewable way. Mediapipe "*mediapipe (version 0.9.0)*" is a crossplatform library that provides ready-to-use machine learning solutions for computer vision tasks. The Tensorflow "*tensorflow (version 2.11.0)*" library is used to create the model. It supports Python language for machine learning. Inside the library, there are various techniques for developing a deep learning model, such as different data entry methods, number of neurons per layer, different layer types, weights, modifiers, constraints, and activations. These tools are used to facilitate learning the active parameters of the network. Therefore, the current model is built using layers containing filters, modifiers and normalizers to train the network and improve the system with the principle of reducing the probability of error [22].

In the study, a 5-layer model with 3 Convolutional Layers and 2 Dense Layers is used with the help of the Keras "*keras version (2.11.0)*" library to define masks. It is a deep learning API written in Python that runs on the machine learning platform TensorFlow. After all the convolution layers, the inputs are downsampled with MaxPooling2D and finally flattened. After flattening, these outputs are sent to Dense Layer and reduced to 2 classes as masked and unmasked. The created model is visualized in Fig. 1. Scikit Learn "*scikit learn (version 1.1.3)*" library is also used to split the trained test data. It is a free software machine learning library for the Python programming language. It features various classification, regression and clustering algorithms including support-vector machines, random forests, gradient boosting, k-means and DBSCAN, and is designed to interoperate with the Python numerical and scientific libraries NumPy and SciPy.

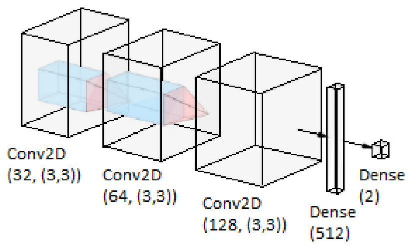

Fig. 1. Training mask detection model layers.

C. *Risk Level Analysis via Fuzzy Inference System in Python*

Fuzzy inference is a method that interprets the values in the input vector and assigns values to the output vector based on some rule set. Two main types of fuzzy inference systems can be applied: Mamdani type [23] and Sugeno type [24]. Mamdani-type inference expects the output membership functions to be fuzzy sets [25]. After addition, there is a fuzzy set for each output variable that needs defuzzification. It is possible and sometimes more efficient to use a single spike instead of a distributed fuzzy set as the output membership function. The main difference between Mamdani-type and Sugeno-type fuzzy inference is that the output membership functions are only linear or constant for Sugeno-type fuzzy inference [26]. In this study, the Mamdani type fuzzy inference system was preferred because it is more interpretable and rule-based. The general structure of the fuzzy inference system is visualized in Fig. 2. To generate the proposed FIS in the Python environment the libraries NumPy and Fuzzy logic are used. "*numpy (version 1.23.5)*" module is used for arrays and data categorization, and "*fuzzy_logic (version 0.0.1)*" is used for create fuzzy rules and generate Mamdami type inference system.

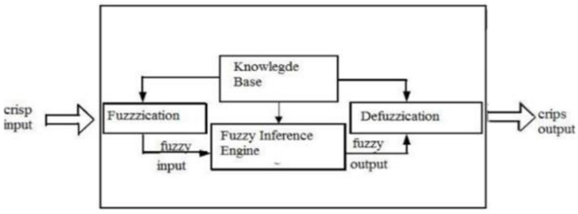

Fig. 2. Fuzzy inference system.

"*High*" statuses are defined regarding the mask wearing status of the person in the image. For the membership of the ambient temperature information, "*cold*", "*medium*" and "*hot*" states are defined. Input membership functions are given in Fig. 3.

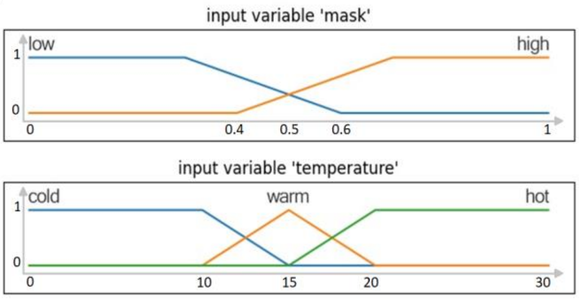

Fig. 3. Mask-wearing rate and ambient temperature membership functions.

As a consequence of the inputs complying with the rules, a risk assessment output is obtained. Output membership function is given in Fig. 4. Accordingly, depending on the mask wearing status and the ambient temperature information membership functions, two output memberships were defined as "*risky*" and "*risk-free*" as a result of fuzzy rules.

The rules written for the fuzzy inference system are given in Table I. The flowchart for proposed hybrid machine learning and fuzzy inference system model to assess indoor virus contamination risk using UAV data is displayed in Fig. 5.

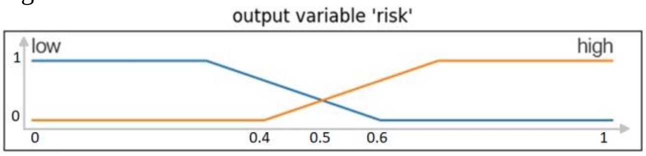

Fig. 4. Risk status membership function.

TABLE I: FUZZY INFERENCE SYSTEM RULES

R1: If	(low mask wearing rate)	⋀	(temp. is cold)	**then** (risky)
R2: If	(high mask wearing rate)	⋀	(temp. is hot)	**then** (risk-free)
R3: If	(high mask wearing rate)	⋀	(temp. is medium)	**then** (risk-free)
R4: If	(low mask wearing rate)	⋀	(temp. is medium)	**then** (risky)
R5: If	(high mask wearing rate)	⋀	(temp. is cold)	**then** (risk-free)
R6: If	(low mask wearing rate)	⋀	(temp. is hot)	**then** (risky)

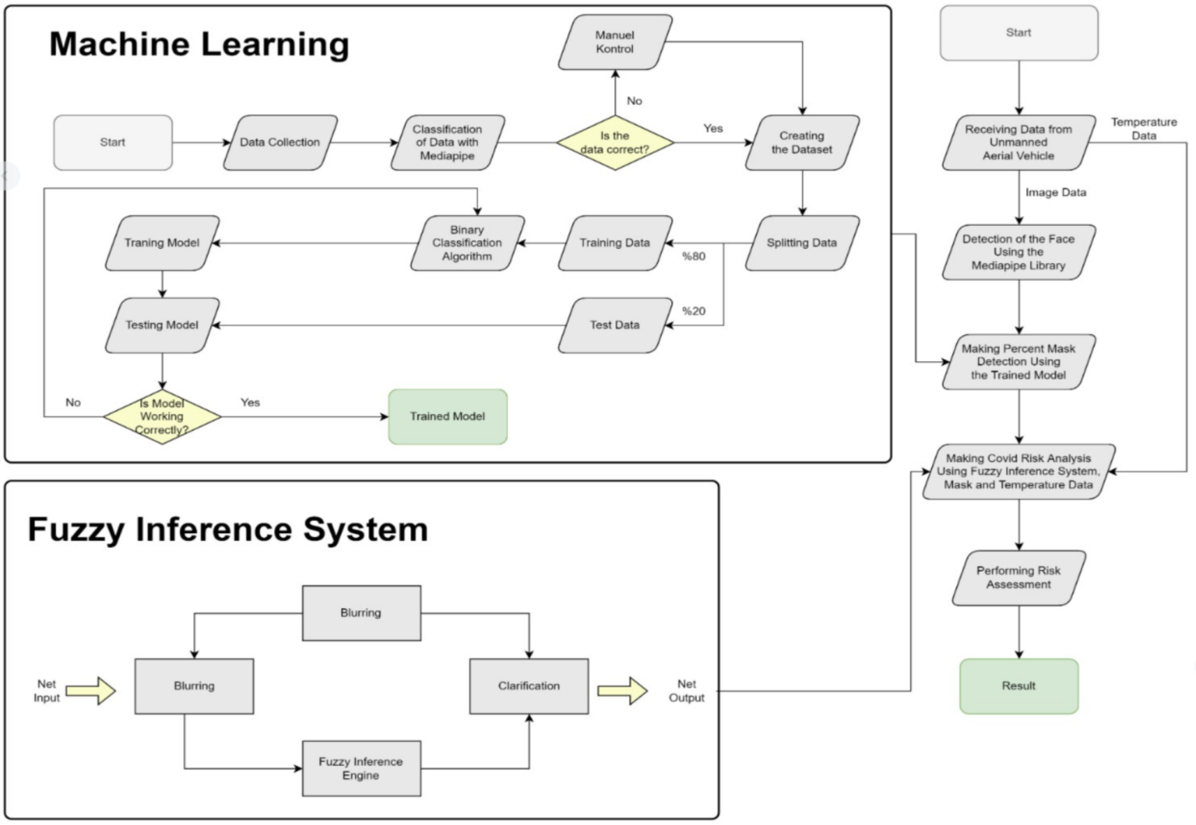

Fig. 5. Flowchart for proposed hybrid machine learning and fuzzy inference system model to assess indoor virus contamination risk using UAV data.

III. Application

In this section, a hybrid machine learning model and fuzzy inference system approach based on the detection of mask use and indoor temperature, proposed in previous section, is applied on UAV images in order to analyze noncontact the risk of virus contamination in indoor areas. For the application, person images are taken by DJI Tello Edu Drone camera. Firstly, the image file (.jpeg) from UAV is processed in the Python environment with the developed multi-layer machine learning model. As a result of this model, a value ranging from 0 to 1 is returned according to the mask wearing status of the person or people in the image. This mask wearing rate is calculated according to the person not having a mask (value 0), using it with the mouth or nose open (value 0–1), and using it to cover the face completely (value 1). In addition, indoor temperature information is obtained by using the temperature measurement feature of the UAV. Afterwards, the mask wearing rate and temperature values are given as input to the fuzzy inference system in Python environment, in line with the rules given in Table I and based on the fuzzy expressions visualized in Figs. 2 and 3. Python is also used for standard function representation. The results of the four trials are detailed below:

In the first experiment, the mask wearing rate of the person in Fig. 6 is 0.01 and the indoor temperature is 26.1 °C. In the light of this information, the output according to the fuzzy inference system rules is given in Fig. 7. As a result, the risk level converges to Rule 6 and turns out to be 0.72 (risky).

In the second experiment, the mask wearing rate of the person in Fig. 8 is 0.62 and the indoor temperature is 26.9 °C. In the light of this information, the output according to the fuzzy inference system rules is given in Fig. 9. As a result, the risk level converges to Rule 2 and turns out to be 0.27 (risk-free).

Fig. 6. Experiment 1 UAV image file with mask wearing rate from trained machine learning model and indoor temperature information from UAV sensor.

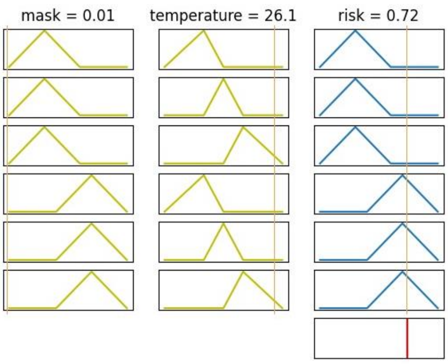

Fig. 7. Experiment 1 fuzzy inference system result.

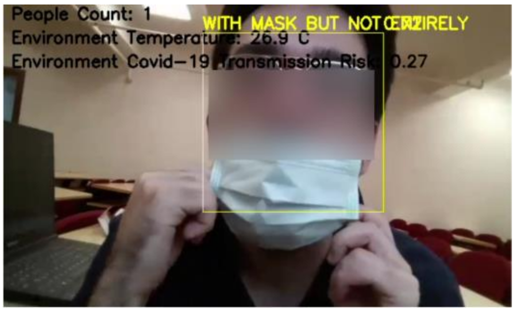

Fig. 8. Experiment 2 UAV image file with mask wearing rate from trained machine learning model and indoor temperature information from UAV sensor.

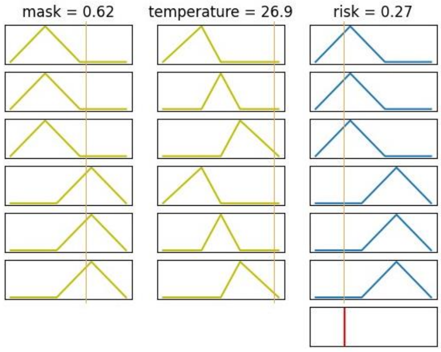

Fig. 9. Experiment 2 fuzzy inference system result.

In the third experiment, the mask wearing rate of both people in Fig. 10 is 0.01 and the indoor temperature is 30 °C. In the light of this information, the output according to the fuzzy inference system rules is given in Fig. 11. As a result, the risk level converges to Rule 6 and turns out to be 1.0 (risky).

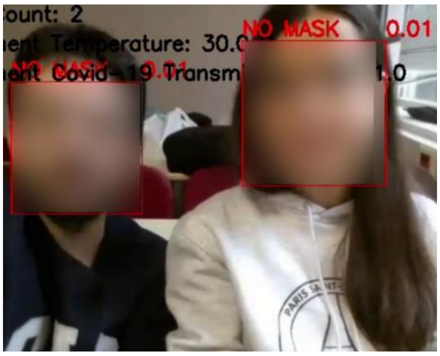

Fig. 10. Experiment 3 UAV image file with mask wearing rate from trained machine learning model and indoor temperature information from UAV sensor.

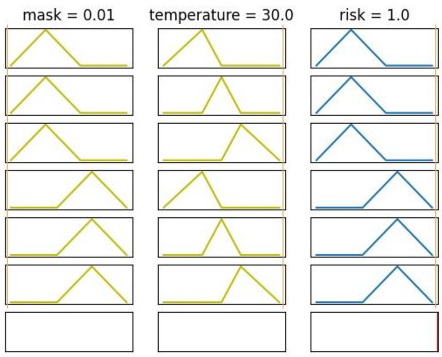

Fig. 11. Experiment 3 fuzzy inference system result.

In the fourth experiment, the mask wearing rate of two people in Fig. 12 is 0.01 and 0.99, and the indoor temperature is 33 °C. In the light of this information, the output according to the fuzzy inference system rules is given in Fig. 13. As a result, the risk level converged to Rule 6 and Rule 2. In this case, the result is 0.65 on average when deducing the Rule 2 risk-free and Rule 6 risky indoor environment. It is an average value according to the output membership function, but it is clear that 0.65 is included in the risky membership status.

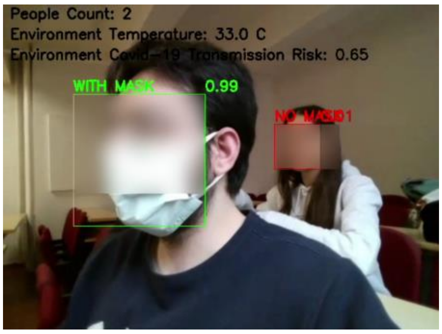

Fig. 12. Experiment 4 UAV image file with mask wearing rate from trained machine learning model and indoor temperature information from UAV sensor.

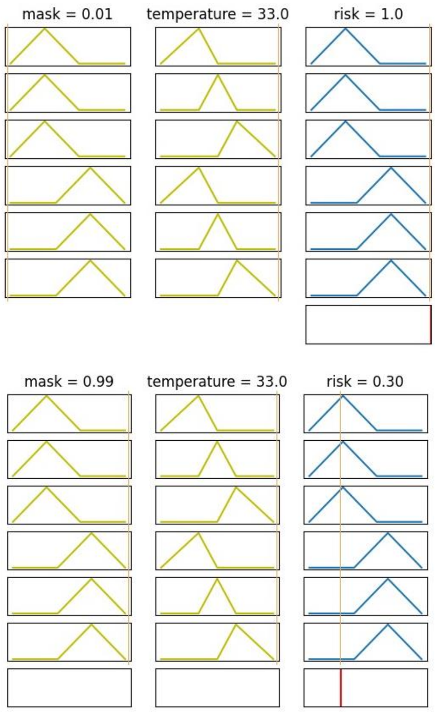

Fig. 13. Experiment 4 fuzzy inference system result.

Due to the worldwide spread and rapid transmission of the Covid-19 virus, researchers have turned to new approaches to assess and prevent the spread of the virus in confined spaces. The position of the mask to cover the mouth and nose on the face and the ambient temperature affect the risk of virus spread and transmission. Based on this problem, this study develops a multi-layer machine learning mode, and evaluates the mask wearing rates of the people photographed with the DJI Tello Edu Drone camera by the trained model. As a result of this model, a number ranging from 0 to 1 is returned, depending on the mask wearing status of the person or people in the image. This number is calculated according to the situation where the person does not have a mask (value 0), use with the mouth or nose open (value between 0–1), and use (value 1) to cover the face. In addition, the temperature information of the environment is obtained by using the temperature sensor of the UAV. The mask wearing ratio and temperature values are entered into the fuzzy inference system in accordance with the rules given in Table I, based on the fuzzy expressions visualized in Figs. 3 and 4. Therefore, it is evaluated whether the indoor environment is risky or risk-free for virus spread according to the mask wearing rate and temperature information. The application of the proposed hybrid model is carried out indoors and the model is tested with four different trials. The comparative results are given in Table II.

TABLE II: COMPARATIVE RESULTS OF ALL EXPERIMENTS.

Experiment No.	Mask wearing rate	Indoor temperature (°C)	Risk Status
Experiment 1	0.01 (low)	26.1 (hot)	0.72 (risky)
Experiment 2	0.72 (high)	26.9 (hot)	0.27 (risk-free)
Experiment 3	0.01 and 0.01 (low and low)	30 (hot)	1.0 (risky)
Experiment 4	0.01 and 0.99 (low and high)	33 (hot)	0.65 (risky)

In the first experiment, it has been studied for a mask wearing rate that has "*low*" membership degree for one person, and indoor temperature information that has "*hot*" membership degree. According to the given fuzzy inference system, the system eventually produces a "risky" membership value that converges to Rule 6.

In the second experiment, it has been studied for a mask wearing rate that has "*high*" membership degree for one person, and indoor temperature information that has "*hot*" membership degree. According to the given fuzzy inference system, the system eventually produces a "*risk-free*" membership value that converges to Rule 2.

In the third experiment, it has been studied for two mask wearing rates that have "*low*" and "*low*" membership degrees for two person, and indoor temperature information that has "*hot*" membership degree. According to the given fuzzy inference system, the system eventually produces a risky membership value that converged to Rule 6.

In the fourth experiment, it has been studied for two mask wearing rates that have "*low*" and "*high*" membership degrees for two person, and indoor temperature information that has "hot" membership degree. According to the given fuzzy inference system, the system eventually produces a "*risky*" and "*risk-free*" membership values that converges to Rule 6 and Rule 2. However, on average, the assessment of the environment is at "*risky*" level.

IV. CONCLUSIONS AND FUTURE DIRECTIONS

The pandemic in 2020 has revealed the importance of non-contact assessment of the risk of contamination in the indoor environment. In this study, hybrid machine learning and fuzzy inference approach has been developed by using the mask wearing rate of the people in the closed area and the ambient temperature information. As a result, the infection risk level of the environment can be determined by six fuzzy inference system rules defined by two input and one output membership function. The image and temperature information obtained from the UAV are evaluated in Python environment, together with the mask usage rate, multi-layer machine learning model and fuzzy inference system. The proposed model is designed to be scalable to simultaneously detect and evaluate many people in a closed area.

For the further benefit, it is recommended to perform the proposed hybrid approach in crowded and open area. The rules in fuzzy inference system can be revised, new membership functions can be defined. Devices that can take high quality photos and have sensitive measurement sensors can be preferred. It is expected that this study will form the basis for non-contact risk measurement approaches and be a source for new approaches to the literature.

Conflict of Interest

The authors declare no conflict of interest

Author Contributions

Furkan Erdi and Esra Çakır developed the technical and theoretical parts. Emre Demircioğlu and Mehmet Ali Taş took place in the experimental study and publication research. All authors contribute equally to the writing of the paper.

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