FaceMask: a Smart Personal Protective Equipment for Compliance Assessment of Best Practices to Control Pandemic

Raffaele Gravina, Ruperto Alexander Lopez and
Pablo F. Ordoñez-Ordoñez

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Raffaele Gravina *
DIMES Dept.
University of Calabria
Rende, Italy
r.gravina@dimes.unical.it
0000-0002-2257-0886

Ruperto A. López
Facultad de Energía, CIS
Universidad Nacional de Loja
Loja, Ecuador
ruperto.lopez@unl.edu.ec
0000-0003-0202-2361

Pablo F. Ordoñez-Ordoñez
CIS, Universidad Nacional de Loja
ETSISI, Universidad Politécnica de Madrid
Loja, Ecuador
pfordonez@unl.edu.ec
0000-0001-8079-7694

***Abstract*—Disposable and reusable face masks represent one of the key personal protective equipment (PPE) against COVID-19 pandemic and their use in public environments is mandatory in many countries. According to the intended use, there exist different types of masks with varying level of filtration. World Health Organization (WHO) has developed a set of best practices and guidelines to the correct use of this fundamental PPE. Nevertheless, many people tend to neglect wearing the mask in presence of other people and to unintentionally overuse the mask before replacement, which results in increased exposure to airborne infections. This paper proposes the development of a smart wearable computing system, consisting of a reusable face mask augmented with sensing elements and wireless connected to a personal mobile device, to recognize correct positioning of the face and capable to monitor other parameters such as usage time. Specifically, we realized a 3D printed mask prototype with replaceable filter and equipped with a small electronic embedded device. The mask collects internal and external parameters including humidity, temperature, volatile organic compounds (VOC) inside the mask, inertial motion, and external temperature and light. Collected data are transmitted over Bluetooth Low Energy to a smartphone responsible of performing signal pre-processing and position classification. Two machine learning algorithms are compared and obtained results from real experiments showed SVM performed slightly better than Naive Bayes, 98% and 97% accuracy, respectively.**

***Index Terms*—personal protective equipment, smart mask, wearable device, body sensor network, machine learning**

I. Introduction

Since the first wave of COVID-19 outbreak, World Health Organization (WHO) has issued recommendations and guidelines to prevent further contagion; social distancing and personal protective equipment (PPE) represent pillar countermeasures; use of face masks in public environments is fundamental given the airborne nature of this respiratory viral infection. Face masks are in fact mandatory in several countries.

WHO has developed a set of best practices and specific guidelines [1] to the correct use of this fundamental PPE. Nevertheless, many people tend to neglect wearing the mask and to unintentionally overuse the mask before replacement, which results in increased exposure to airborne infection.

This paper proposes a wearable computing system, composed of a smart face mask and a mobile phone, which captures information from multiple sensors embedded inside and outside the mask to recognize its correct use (i.e. correct positioning of the face, properly covering mouth and nose) through a machine learning method. Sensor data is collected by the mask and sent via Bluetooth Low Energy (BLE) to the smartphone which extract significant features and performs the classification task.

II. Related Work

With the arrival of COVID-19, the interest on smart wearable and mobile devices to face, in different ways, pandemic situations is significantly increasing. Contact tracing is fundamental to promptly identify the recent network of contacts with a diagnosed positive person and most countries implemented solutions based on smartphone apps able to detect proximity among users. Personal hygiene procedures are also crucial to limit the risk of being infected after touching contaminated objects and surfaces; indeed, use of hand gel sanitizer and proper hand washing are among best practices and become, in several environments, mandatory procedures. Smart rings are being developed [2] to assess compliance to hand hygiene procedures in specific environments such us infectious disease hospital departments.

However, one the most fundamental equipment to limit the diffusion of the virus is undoubtedly the face mask. According to its material, it can drastically reduce droplets and aerosol and, at the same time, significantly increase the level of personal safety against contaminated particles in the air. Although the development of smart face masks is in early stage, a few but promising solutions have been recently proposed. In [3] the authors proposed a mask with activated carbon HEPA filters and integrated Bluetooth headphones; however, no sensors were used to monitor filtering efficacy or other usage parameters. An active protective mask is reported in [4] based on self-powered triboelectric nanogenerator in which the viruses are killed in the electric field, but this system also lacks of sensing and monitoring capabilities. Another smart mask with electrical active fabrics was proposed to maximise particulate matter filtering during inhaling process and harvesting the energy generated by exhaling [5].

In [6] the authors proposed a smart medical mask to monitor body temperature and strain on the face to avoid irritation and bruising caused by tight sealing. Although the work is promising, a mass production would be limited by the fabrication technique that employs 3D face scanning for precise positioning of temperature and strain sensors on the mask with aerosol jet printing.

A peculiar active protection smart mask is proposed in [7]. Specifically, the mask embeds a particulate matter sensor and an active mitigation device that, upon the detection of droplets proximal to the mask, sprays a mist (from an embedded liquid reservoir) that binds to them, increasing their mass, so forcing the droplets falling quicker to the ground. Other studies aimed at the detection of respiratory diseases and monitoring of vital parameters in infected, hospitalized patients by means of face masks augmented with multiple physiological sensors [8], [9]. Specifically, they can monitor abnormal body temperature, heart rate, blood oxygen saturation, blood pressure, and respiration rate, associated with symptoms of pneumonia caused by coronaviruses.

In contrast with previous literature, we propose a machine learning approach to recognize proper positioning of the mask on user's face.

III. Materials and Methods

The concept of this work is the augmentation of reusable face masks composed by rigid or semi-rigid structure and replaceable filtering elements with an embedded sensing and computing device.

The proposed machine learning method consists of hierarchical recognition composed of two classification phases. The first phase is a binary classification to detect whether the mask is carried by the user; only data generated by the accelerometer sensor is used at this step. The second phase consists of a multi-class learning method that allows to detect if the mask is put on the face, and in particular to assess if it is being used correctly (i.e. correctly positioned to cover both mouth and nose). For this second step, in addition to the accelerometer signals, also data generated by the light, humidity and VOC sensors are taken into account.

A. Smart Mask Prototype

Our smart mask prototype is based on the mask model developed by Copper3D [10]. However, it was not possible to simply reuse that model due to the lack of proper housing for the electronic devices. We used Ultimaker Cura to design the mask model for 3D printing, as shown in Fig. 1. Differently to the original Copper3D model, our mask has housing for a lithium battery located on the left side, as shown in Fig. 1a. On the opposite side, there is the housing for the main-board with BLE radio and the accelerometer, light, and environment temperature sensors, as shown in Fig. 1c. Finally, the second sensor-board with VOC, humidity, and temperature is located inside the mask as shown in Fig. 1b. A detailed list of specifications is reported in Table I.

TABLE I: Mask Datasheet

Mask without circuits	**75gr**
Mask with circuits	115gr
Size	102.6x97.1x135.2mm
Print temperature	200°C
Build plate temperature	60°C
Cost for printing 3D Mask	$150,00
Time invested for printing	21h 16min
Wall thickness	0.8mm
Layer height	0.2mm
Upper/lower layers	4/4
Material	PLA

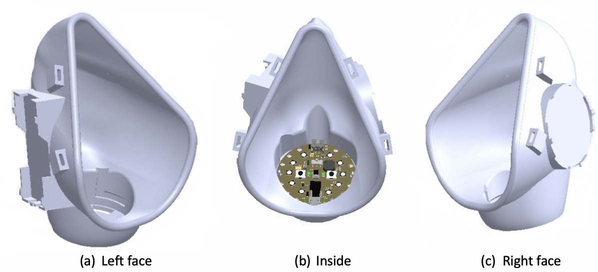


Fig. 1: Different perspectives of 3D mask model.

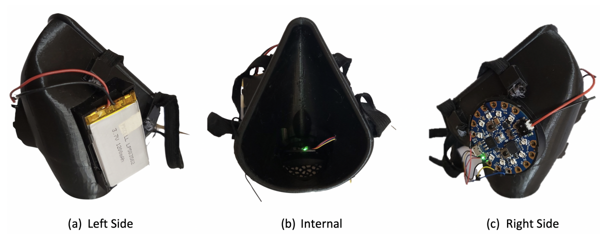


Fig. 2: Actual prototype of FaceMask.

It is important to mention that the developed mask has an replaceable filter system as shown in Fig 4, which is placed inside the mask where the humidity sensor is located. This system has three elements: the grille (see Fig. 4a), the interchangeable filter (see Fig. 4b) and finally the lock (see Fig. 4c) that rotates clockwise to fit the filter in place. Thanks to the choice of Adafruit Bluefruit as prototyping platform, it becomes easy to assemble and connect the various components. Thus, in case of accurate cleaning (e.g washing) of the mask skeleton, removing the electronics is easy and fast.

As aforementioned, the prototype, shown in Fig. 2, is based on the Adafruit Circuit Playground Bluefruit embedded platform; a detailed list of prototype specifications is reported in Table II.

We developed the embedded software on the Bluefruit mainboard with CircuitPython [11], which is based on the Python programming language.

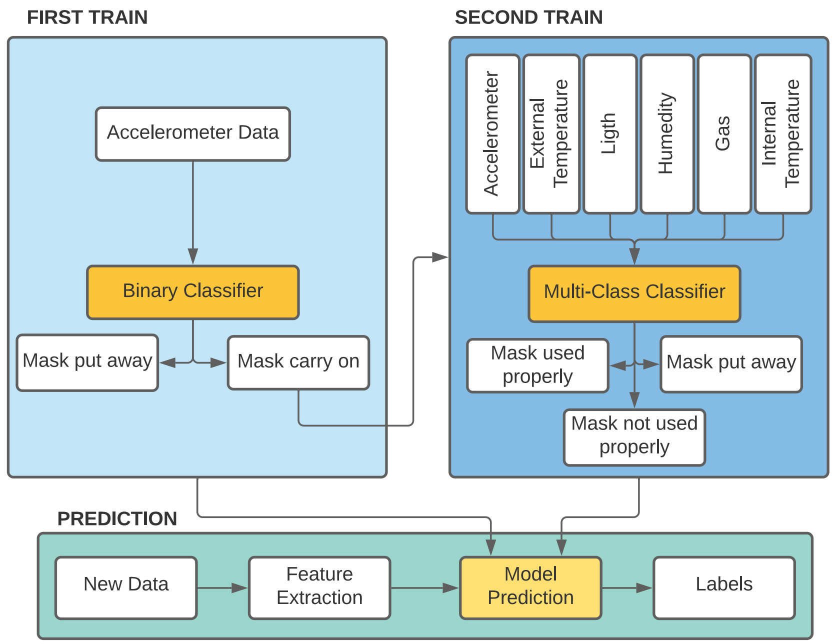


Fig. 3: Workflow of the proposed recognition method.

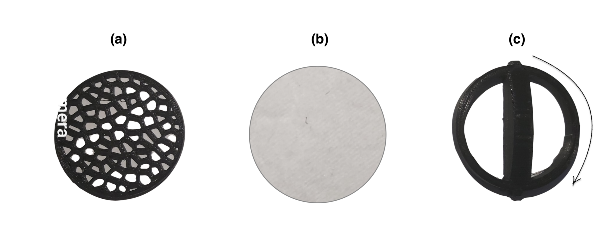


Fig. 4: Interchangeable Internal Filter system

TABLE II: Specifications of the smart mask prototype

External Board	Adafruit Circuit Playground Bluefruit
External Sensors	- Motion sensor (LIS3DH 3D accelerometer with free-fall detection) - Temperature sensor (thermistor) - Light sensor (phototransistor)
Internal Board	Adafruit BME680
Internal Sensors	- Humidity with ±3% accuracy - Temperature with ±1.0°C accuracy - Volatile organic compounds (VOC)
Micro controller	nRF52840 Cortex M4
3D printing Material	Polylactic Acid (PLA)
Battery	- Lithium Ion Polymer - 1200mAh at 3.7V nominal
Connectivity	Bluetooth Low Energy
User Interface	- Mini speaker with class D amplifier (7.5mm magnetic speaker/buzzer) - 10 x mini NeoPixel multicolour LEDs

The circuit design is depicted in Fig 5, where the connections between the components is shown. Adafruit components can use Qwiic boards for preliminary prototyping, to easily connect sensors and controllers from one board to another, when used with Qwiic the wire colours meaning is shown in Table III.

TABLE III: Colour Codification (I2C Protocol)

Red	3.3VDC Power
Black	Ground
Blue	I2C SDA Data
Yellow	I2C SCL Clock

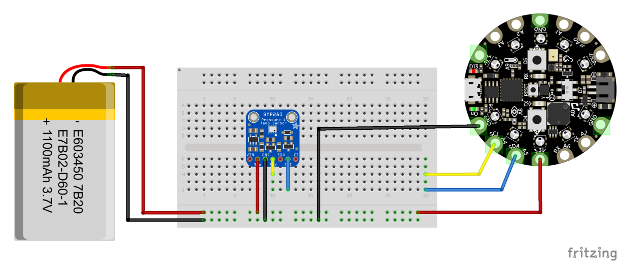


Fig. 5: Smart FaceMask Circuit Design

B. Machine Learning Process

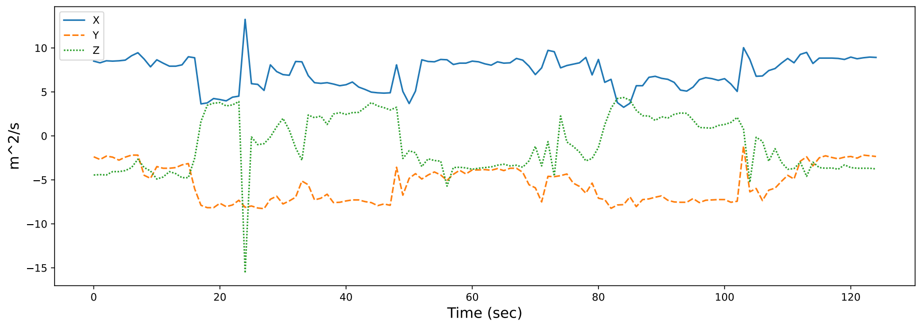
As aforementioned, our approach is based on two classification phases. The complete workflow of the proposed machine learning process is depicted in Fig. 3.

The first model is generated to realize a binary classifier. In particular, only when its output indicates the mask is carried on by the user, the second classifier is executed.

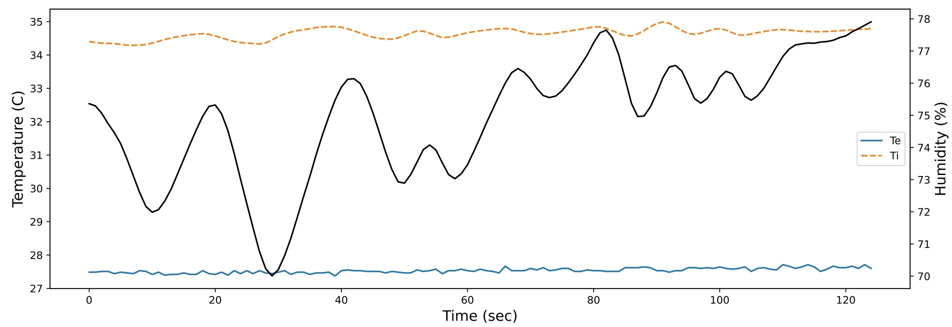
Both models follow a traditional training flow: data collection, feature extraction, model training, and model evaluation. However, for the sake of graphical clarity, they are not presented in the diagram of Fig. 3.

Data collection - there are two separate data collection steps. The first one collects data only from the accelerometer, as shown in Fig. 3, to perform the binary classification.

The second step collects data from the other sensors in addition to the accelerometer, as shown in Fig. 3. In this



(a) Accelerometer signal when coughing



(b) Temperature Internal, External and Humidity when coughing

Fig. 6: Signal when coughing occurs

second stage, the goal is to collect the necessary data to train the multi-class learning machine that will recognize if the smart mask is properly used as in Fig. 7. Ground-truth information on the appropriate use of face masks for pandemic control are provided by WHO [1].

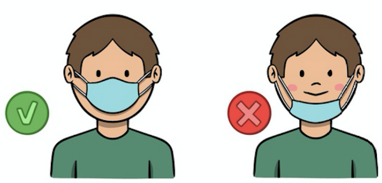


Fig. 7: Positioning of the mask: correct (left) vs incorrect (right).

Preprocessing and Features Extraction - We use the OpenRefine tool to perform the preprocessing for noise reduction and outlier removal. As shown in Fig 6b, it is evident that when the user wears the mask, the internal temperature raises wrt the external temperature; in addition, it is interesting to observe a clear pattern in the humidity signal during breathing and coughing, which suggests the possibility to monitor breathing rate and regularity by analyzing the internal humidity. In short, from the correlation matrices shown in Fig 8, Fig 9, and Fig 10, it can be noted that there are signals that are positively or negatively correlated, and other ones that are uncorrelated. See .

In this work, feature extraction is executed with Python Time Series Feature Extraction Library (TSFEL) [12]; in particular, in addition to common statistical and morphological signal attributes, the following time-domain features were extracted: Area under the curve, Centroid, Absolute energy, Autocorrelation, Total energy among others.

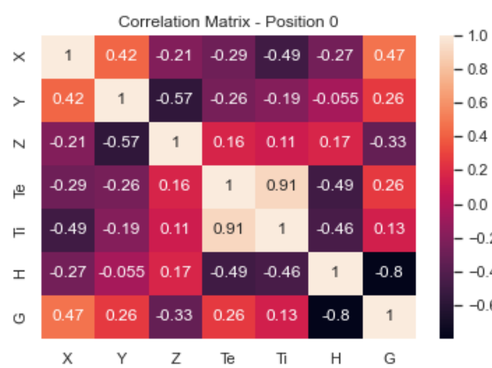


Fig. 8: Correlation Matrix - Mask put away

Feature Selection - it is essential to identify the most significant subset of features to train the classification model. Various selection techniques are successfully applied to sensor data features [13]. In this work, we use Randomised Decision Trees (ExtraTrees) to select the most significant feature set.

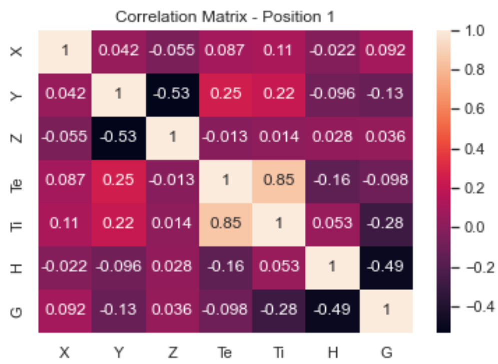


Fig. 9: Correlation Matrix - Mask used properly

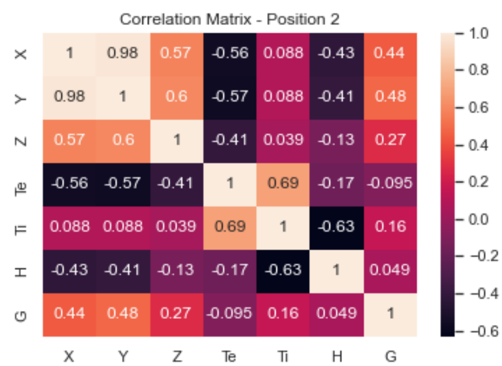


Fig. 10: Correlation Matrix - Mask not used properly

Classification - the implementation of our machine learning model is based on the comparison of two well known methods, namely Support Vector Machine (SVM) [14], [15] and Naive Bayes [16] which are frequently applied in the context of human activity recognition, wearable and mobile computing.

IV. Experiments and Results

Experimental evaluation of the proposed method was carried out with the mask prototype described in the previous section. The experiments were carried out in a private room during actual smart working desk activities, i.e., given the current situation, in a safe environment for the participant. A current limitation of the work is the limited participant sample (one male and one female young healthy subjects) that is bounded, for obvious hygienic reasons, by the number of masks we were able to prototype. It is worth mentioning that for each experiment, it was necessary to clean the masks.

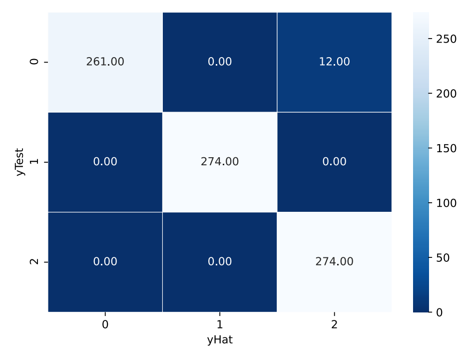
The experiment protocol consists of data collection for each case (i.e. i) *mask put away* - in this experiment is left of the desk, ii) *mask carried on but not worn* - in this experiment stored on a backpack worn by the participant, iii) *mask used improperly* - in this experiment covering just the mouth, and iv) *mask properly used*) Each case is recorded for 30 minutes with one hour of rest between correct and incorrect use. Five complete trials are executed by each participant.

We therefore obtained two datasets respectively for the binary classification (169270 samples) and the multi-class classification (174646 samples); both still contain raw data.

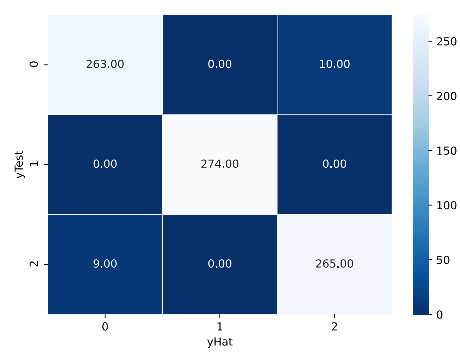
For model training and evaluation, both datasets are split in 80% for training and 20% for testing, paying attention to maintain class balance, since an unbalanced class leads to poor evaluation results.

According to the preliminary results, SVM and Bayes Naves algorithms show similar performances for the first binary classification step, with 96% recognition accuracy on average.

As it can be observed with the confusion matrices of Fig. 11, in the second multi-class classification step, instead, SVM classifier slightly outperforms Bayes Naves algorithm, with average recognition accuracy of 98% and 97%, respectively.



(a) SVM Confusion Matrix



(b) Naive Bayes Confusion Matrix

Fig. 11: Confusion matrix of second phase, multi-class classification.

V. Conclusions and Future Works

In this work we have presented a wearable computing system consisting of a smartphone and a smart face mask that captures accelerometer, light, temperature, humidity and VOC data to detect when the mask is worn and in particular to recognize its correct positioning on the face. Two-phase classification method has been proposed, a 3D printed prototype has been realized and augmented with Adafruit Bluefruit embedded platform. The proposed system was experimentally evaluated by comparing the positioning recognition performance using SVM and Naive Bayes algorithms. According to our preliminary results, SVM showed slightly superior accuracy than Naive Bayes.

We are currently devoting efforts to realize more prototypes so to collect additional data from other subjects and obtain more robust results. In addition, we are investigating the capability of the proposed device to act as an alternative solution for contact tracing, given that it also includes a Bluetooth radio and RSSI-based proximity estimation is feasible. Furthermore, we are implementing a usage timer with a user-friendly feedback using the multi-colour LEDs of the mainboard to notify the user when it is time to change the filtering element of the mask. Finally, as future work we plan to analyze the signals collected from internal sensors (i.e. in particular humidity and VOC) to indirectly monitor relevant vital parameters such as breathing rate and detect coughing.

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