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SPECIAL SECTION

Analyzing and improving tools for supporting fighting against COVID-19 based on prediction models and contact tracing

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Abstract. In the paper, we are analyzing and proposing an improvement to current tools and solutions for supporting fighting with COVID-19. We analyzed the most popular anti-covid tools and COVID prediction models. We addressed issues of secure data collection, prediction accuracy based on COVID models. What is most important, we proposed a solution for improving the prediction and contract tracing element in these applications. The proof of concept solution to support the fight against a global pandemic is presented, and the future possibilities for its development are discussed.

Key words: COVID-19; prediction models; contact tracing.

1. INTRODUCTION

At the time of the COVID-19 pandemic, the digital potential is being exploited in various ways to fight and reduce disease and mortality. Mobile applications and web tools have great potential when most of us have access to the Internet and are still carrying a smartphone. Today, almost a year after the beginning of the global pandemic, there are several dozen such solutions to support impact management and health services. They differ in their approach, their implementation, and their purpose. Some only collect symptom data, others aim at tracking contacts and signaling contact with the positive person. All have in common the fact that they support the fight against a global pandemic.

In the paper, we are analyzing and proposing an improvement to current solutions supporting fighting with COVID-19. We analysed the most popular anti-COVID tools and COVID prediction models. We addressed the issues of secure data collection, prediction accuracy based on COVID models. What is most important, we proposed a proof of concept solution for the improvement of the prediction and contract tracing element.

The remainder of this paper is structured as follows. In the related work section, we present the currently used centralized and decentralized approach for tracking people contacts and potentially warning them of contact with a positive infected person. We present the most popular applications supporting fighting COVID and prediction models. In the next chapter, we introduce our proof of concept solutions, which address some issues and concerns regarding currently used approaches. Our analysis is focused on four elements. First is data collection with security concerns, the second is a comparative analysis of prediction-based COVID models, the third is the contact tracing element when we urge to integrate advanced localization techniques. Fourth element is a short analysis of the utilisation of 5G and Internet of Things. The paper ends with conclusions for future work.

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2. RELATED WORK

There are currently two approaches for tracking people's contacts and potentially warning them of contact with a positive person. Some countries apply a centralized approach to COVID-19 contact tracing. These countries apply solutions based on network traffic, location data collection, and digital footprint in general [1]. This is the approach taken, for example, by Israel, where the government has approved network-based tracking of citizens and their contacts [2]. South Korea has also taken a similar approach to this issue, where we see excellent results in the fight against the pandemic. They have abandoned the use of tracking applications and have built a system for the national collection of location data of citizens from various sources, i.e., data on payment transactions and Internet traffic [3]. Based on the information collected in this way, the system processed the data and provided residents with SMS messages informing them of potential contact and providing basic information about a positive person in their area. Currently, European countries do not officially apply this type of approach [4]. Decentralized systems are intended to preserve the privacy of those who are being followed, as opposed to centralized systems [5, 6]. This approach uses the dissemination of mobile applications to residents and the collection of information from them about their location in isolation from their personal data

[7]. There are already several protocols used in many mobile applications. For example, systems based on Bluetooth Low Energy (BLE) technology are such privacy-conscious solutions [8]. They demonstrate the proximity of another user's device to ours without collecting their personal data. Such devices send out anonymous keys and collect a list of the keys of other users with whom they have had contact. If one of the users turns out to be positive, they receive a notification about potential contact with the positive person and a recommendation for testing and isolation [9]. Currently, Google and Apple offer governments the use of their Exposure Notification API to emulate this type of solution in government applications [10].

2.1. Current Tools

The official Polish application notifying of exposure to the coronavirus, designed in cooperation with the Chief Sanitary Inspectorate is called "STOP COVID ProteGo Safe". The application is intended for use in Poland and consists of two modules. The first one is a module enabling the self-control of health conditions. It is a kind of a "log", which allows us to verify on an ongoing basis whether and in which group we are at risk of infection. It is a solution based on the guidelines of the World Health Organisation (WHO). The second module is to scan the environment and communicate in case of a risk of contact with the virus. Main functionalities include user contact tracking based on the previously mentioned Exposure Notification API developed by Google and Apple. Uses Bluetooth Low Energy to exchange keys between the devices. It performs an infection risk assessment test. It allows recording health status and symptoms creating a register of potential risk of COVID-19 infection and it does not collect or share user data and it is anonymous to use.

The next example is COVID-19 Screening Tool, an application that allows for independent execution of the screening protocol and self-testing algorithm (Fig. 1). The user answers a series of questions. Based on the answers, the algorithm provides the user with information about what steps he should take. The whole protocol is based on the open source project CDC COVID-19 Health Bot created by Centers for Disease Control and Prevention, the US Federal Emergency Management Agency, and with support from the US Government with functionalities as follows: The possibility of carrying out a self-review of your current state of health. It provides references to other recommended sources of knowledge and it is anonymous to use. The application is available on smartphones with IOS and as a website. In addition, many different websites and applications use the same CDC algorithm but enclose it in a different visualization.

Another application is CDC COVID-19 Health Bot. The purpose of the CDC self-checker algorithm is to help you decide to seek appropriate medical care and further steps based on your condition (Fig. 2). This system is not intended to diagnose or treat a disease or other condition, including COVID-19. The algorithm proposes a result based on the answers given by the user, e.g., age, presence of chronic diseases, symptoms characteristic of infection, or being in the company of patients or in medical facilities.

Next application is NHS COVID-19. The official government application for the people of England and Wales to contact tracing and facilitate access to coronavirus tests. It is part of the government's strategy to combat the pandemic. The contact tracing collection algorithm is based on the Exposure Notification API by Google and Apple. It is a kind of equivalent to the Polish COVID STOP application in Great Britain. Its functionalities include: Tracking: to know if you have been near other users of the application who have tested positive for coronavirus. It provides alert: informs you of the level of risk associated with the coronavirus in your postcode district. It can provide notification if you have visited a place where you may have had contact with the coronavirus using a simple QR code scanner. It can test the symptoms of the coronavirus and helps order a test.

2.2. COVID Prediction Models

In this section, we will present COVID Prediction Models used in anti-COVID applications. First is the project DECODE – (Data driven COVID DEtection) which was developed at the Silesian University of Technology in cooperation with Specialist Hospital No. 1 in Bytom (Figs. 3–5). Its main objective is to provide a tool available online and enable quick identifica-

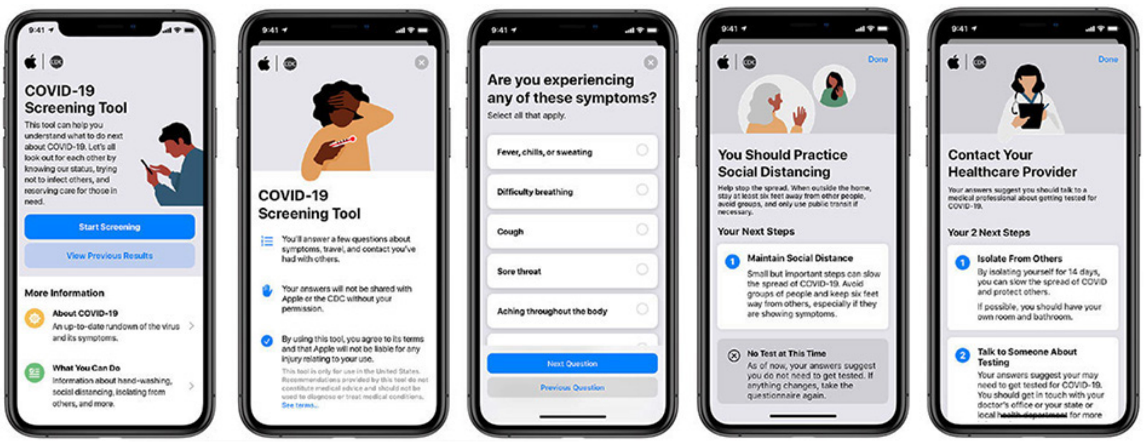

Fig. 1. COVID-19 Screening Tool as mobile app [11]

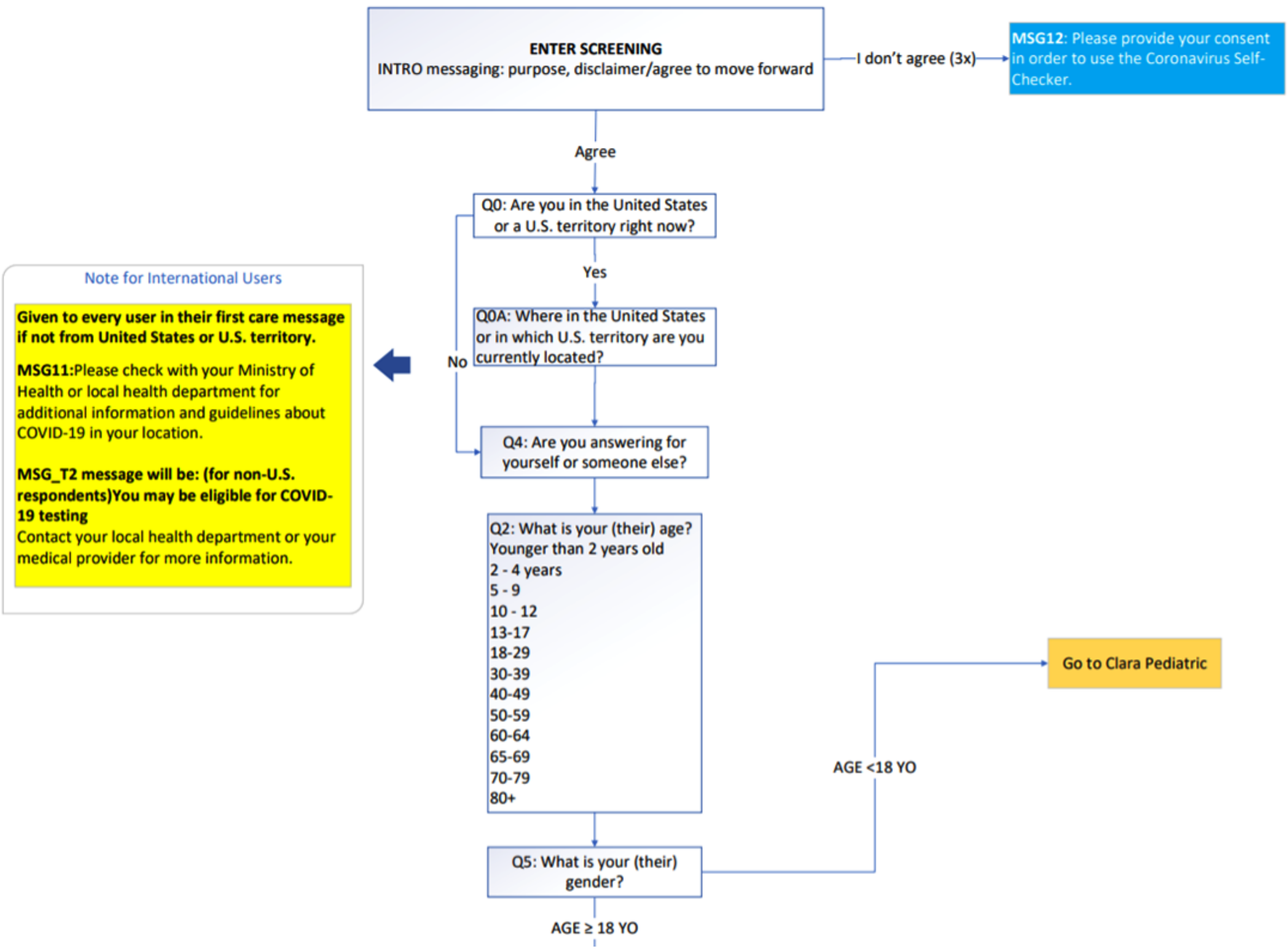

Fig. 2. Part of CDC COVID-19 Health Bot algorythm [12]

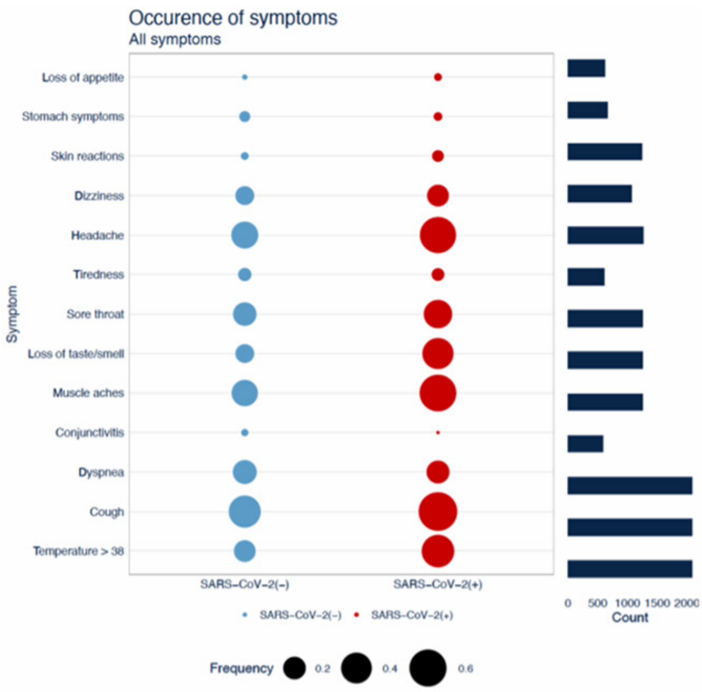

Fig. 3. DECODE – ocurrence of symptoms [13]

se: 0.997 LR+: 1.379
sp: 0.277 LR–: 0.011
PPV: 0.38 DOR: 125.364
NPV: 0.995

	truth	
prediction	COVID (+)	COVID (–)
COVID (+)	325	530
COVID (–)	1	203

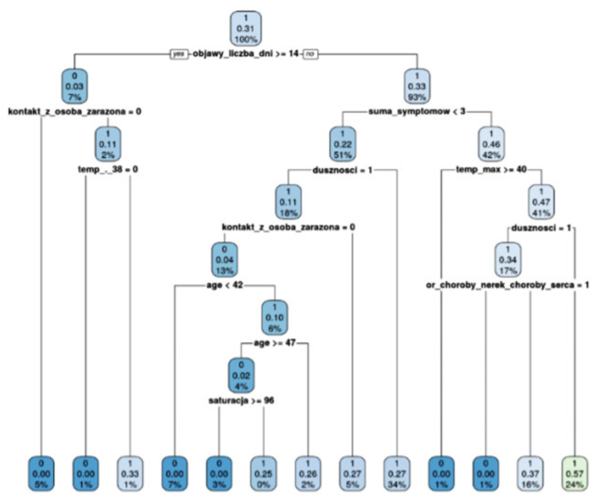

Fig. 4. DECODE – Example of a decision tree for different costs of misclassification. Optimisation attempts: sensitivity (se), specificty (sp), PPV, NPV [13]

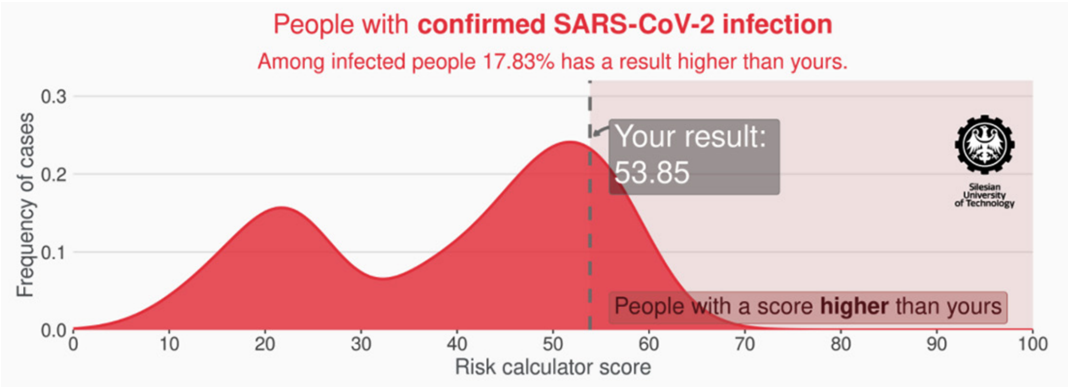

Fig. 5. DECODE – example result info [13]

tion of people actually infected with the SARS-CoV-2 virus. To maximize the effectiveness of the algorithm, the creators decided to extend the number of values checked by it. The project is currently being developed by the team. New data is still being added and its accuracy is increasing. It is a kind of calculator of the probability of coronavirus infection. DECODE is a symptom checker tool to assist patients and family doctors in preliminary diagnosis and early detection of SARS-CoV-2. It uses a machine learning model to check symptoms and provides information that could be helpful to determine whether you need to be tested for SARS-CoV-2. To understand and learn the epidemiological-demographic cross-section of COVID-19 patients, a group of around 2000 people was gathered. They were subjected to PCR tests for coronavirus. Then, questionnaires were collected from them asking about the presence of chronic diseases, basic data such as age, drugs taken, and the presence of symptoms characteristic for SARS-CoV2 infection. From these questionnaires, important data were extracted and collected in the form of a database. Statistical analysis and machine learning methods were conducted on these data. On the basis of the analyses, significant correlations between disease symptoms and coexisting diseases, and the probability of COVID-19 infection were found. It was also possible to obtain a ranking of the importance of decision-making features in machine learning. Many interesting relationships were found. The development and continuous analysis of the growing database of results are still ongoing. The data obtained from patient questionnaires were analyzed statistically. Then, on this basis, key symptoms were selected and with the help of machine learning and decision trees, the paths with the most optimal values were found. The key was that the main focus was to identify the actually infected persons with the greatest possible certainty. Unfortunately, this is at the expense of some people who will be assessed as positive with this model despite the actual negative result. In this way and at such a cost, this is the most reasonable approach. The following are the key passages of the analysis carried out.

In addition to the results (positive/negative), the tool offers statistical data on the results obtained. Additionally, a scale is indicated with which it can be assumed that for values above 40 the user of the survey has a highly probable positive test result.

Another Model is based on the paper published in Nature Medicine discussing real-time tracking of self-reported symptoms to predict potential COVID-19 and is described by formula (1) [14]. The authors, thanks to the mobile application, gathered among over 2.5 million users their data about potential symptoms felt. Among them, less than 18.5 thousand reported taste and smell loss. Such people were higher in those with a positive test result (4668 of 7178 individuals; 65.03%) than in those with a negative test result. (2436 of 11,223 participants; 21.71%) [odds ratio = 6.74; 95% confidence interval = 6.31–7.21]. Based on this data and its statistical analysis, the aim was to propose a model that would allow a quick prediction of the test results based on a short questionnaire. The authors selected a set of symptoms that offer the best prognosis for the model and gave the highest score to the symptoms of the loss of smell and taste. Based on statistical data, they indicated this symptom as the highest scored in the proposed linear model.

$$
\begin{aligned}
&\text{Prediction model} = -1.32 - (0.01 \times \text{age}) \\
&+ (0.44 \times \text{sex}) + (1.75 \times \text{loss of smell and taste}) \\
&+ (0.31 \times \text{severe or significant persistent cough}) \\
&+ (0.49 \times \text{severe fatigue}) + (0.39 \times \text{skipped meals}). \qquad (1)
\end{aligned}
$$

The symbols have been binary coded. 1 indicates their presence, 0 their absence. In addition, the gender has also been captured in this way, where 0 means a woman and 1 means a man. The obtained value is then transformed into the predicted probability using $\exp(x)/(1+\exp(x))$ transformation followed by assigning cases of predicted COVID-19 for positive probability >0.5 and control for negative probabilities <0.5 [14].

Between 24/03 and 21/04 of 2020, 2 450 569 UK and 168 293 people from the USA reported symptoms via smartphone app. Participants in the United Kingdom with a number of 789 083 (32.2%) showed one or more potential symptoms of COVID-19. A total of 15 638 app users from the UK and 2763 from the US reported that they had performed and received the results of the SARS-CoV-2 RT-PCR test. In a group from UK, 6452 participants reported having carried out the SARS-CoV-2 RT-PCR test. The test was positive and 9186 participants had a negative test. In the UK group, with 6452 participants who tested positive for SARS-CoV-2, 4178 64.76% smell and taste loss was noted, compared to 2083 out of 9186 participants (22.68%) who obtained a negative result (quotient of chance (OR = 6.40; 95% confidence interval (CI = 5.96–6.87; $P < 0.0001$ after adjustment for age, gender and Body Mass Index (BMI)). The authors reproduced this result in the USA dataset of participants who were tested for SARS-CoV-2 (corrected OR = 10,01; 95% CI = 8,23–12,16; $P < 0,0001$) and combined corrected results using a meta-analysis of the permanent effects of the inverse variance (OR = 6.74; 95% CI = 6.31–7.21; $P < 0.0001$). Comparative analysis of these models will be done in the next chapter.

3. IMPROVEMENT OF SOLUTIONS FOR FIGHTING COVID

In this section we present a proof of concept tool to support the fight against the global pandemic COVID-19. While presenting the main functionalities, we will analyse and propose an improvement to the currently used solutions. Application main functionalities consist of three elements. The first element is the collection and processing of data collected from the user. The second element is the part responsible for the prediction of the COVID-19 test result based on the answers collected in the application survey. Prediction is based on a model created as a result of scientific research, the use of machine learning, and artificial intelligence. The third element is contact tracing between users. The aim is to warn about potential contact with an infected person, so that appropriate measures can be quickly applied to such a person and reduce the risk of further transmission of the infection. The details of the above mentioned elements are discussed in the following sections.

3.1. Data collection

To achieve the goals set for the application, it is necessary to collect data from the user and beyond. Taking into account that the work focuses on the COVID-19 combat application concept, general ideas and assumptions about data collection and processing will be described. The data that the application will process can be divided into three categories:

- **User's medical data** – this generally includes information about age, gender, chronic diseases, or test prediction results.
- **User location data** – this generally includes information collected from the device's sensors, such as GPS location, Wi-Fi connections, mobile network connections, or light sensor indications.
- **External data** – this generally includes information combining location information with data on public places available on the network, such as shops, pharmacies, medical centers, or public transport vehicles.

A collection of location data would intercept, at a fixed interval, information about the location of the device, namely the exact longitude and latitude. The geographical location should also support the collection of information about the connection to mobile Wi-Fi points, such as those found in trams, public transport, buses, galleries, and retail shops. This would support obtaining the most accurate location data possible. It would also support the element of constantly tracking smartphone connections to the mobile network provided by specific base transceiver stations (BTS). The signal strength, the number of BTSs connected, and other details of the established connection would be collected. In the case of external data collection, which would define the public places visited by the user, there would be publicly available information about the name, address, or purpose of the location. For example, the user records the presence of a given point in an urban space. Combining this with specific data about the fact that it is, for example, a small grocery shop, would allow the user to assign a visit to that point to the collection. When other users also register their presence at a given point, it will be possible to analyze, on the basis of the available data and the possibilities offered by machine learning, whether the user has had contact with another user and, going further, whether he has had contact with a potentially infected user [15]. It should be pointed out that the potential user of such an application would have to be convinced of its security. Nowadays, the subject of the threat to private data is raised very often and reasonably [16]. Therefore, the application should use full anonymisation of data, they should not be directly linked to specific personal data, such as name and surname, PESEL or ID card number. However, if wanted to introduce it into general use, it would be necessary to ensure that the server on which the database and tools supporting the processing of these data would meet the highest standards at present. Another element which should be taken into account is compliance with national law, such as the constitution, or with the Conventions on Human rights, which explicitly treat the right to data privacy, and medical data in particular [17].

3.2. Prediction based on COVID Models

One of the main elements of the application design to support fighting against COVID is the prediction of the test result for the presence of coronavirus infection. Such functionality is crucial as it allows to determine the potential risk of infection [18]. This allows the users of the application to consciously avoid contact with and infection of other healthy people. This measurably limits the spread of infection outbreaks. The predictive model, like any system, is flawed, but it has been deliberately adjusted and determined so that virtually every actual positive user is marked as positive. This bears the cost of marking as potentially positive people who are actually negative. However, such a strategy is fully justified, as it is far better to isolate a larger section of the population than to lead to a situation where positive people infect further individuals and exponentially increase the number of patients in an area. Therefore, this element of the application aims to build the user's internal awareness and to offer them clear recommendations for behaviour.

To select the most suitable model for the predictive element of the proposed application concept, the results of the mentioned in related work section models were compared. A table of 10 randomly selected cases was prepared (Table 1). Symptoms were marked in a binary way, where 1 means presence and 0 means absence. Similarly for gender values, where 1 means male and 0 means female. It has been taken into account that

Table 1
Selected cases to compare models

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	Case 9	Case 10
Age	55	25	35	65	45	45	25	55	65	35
Sex	1	0	1	0	1	0	1	0	1	0
Contact with an infected person	not known	not known	not known	not known	not known	yes	not known	not known	yes	yes
SYMPTOMS										
Temperature > 38°C	0	0	0	0	0	0	1	0	1	1
Cough	0	1	0	1	1	1	0	0	1	1
Dyspnoea	0	0	0	0	0	0	0	0	0	1
Max. observed temperature [°C]	36.6	36.6	36.6	36.6	36.6	36.6	38.5	36.6	39	38.5
Muscle pain	0	0	0	0	0	0	1	0	1	1
Headache	0	0	0	0	0	1	0	1	0	0
Stomachache	0	0	0	0	0	0	0	0	0	0
Diarrhea	0	0	0	0	0	0	0	0	0	0
Sore throat	0	0	0	0	0	0	0	0	1	0
Dizziness	0	0	0	0	0	1	0	0	0	0
Loss of smell/taste	1	0	1	0	1	0	0	1	0	1
Malaise (feeling tired)	1	1	1	1	1	1	0	1	0	1
Loss of appetite	0	1	0	1	1	0	1	0	1	0
Skin symptoms	0	0	0	0	0	0	0	0	0	0
CHRONIC DISEASES										
Hypertension	0	0	0	0	0	1	0	0	0	0
Diabetes	0	0	0	0	0	0	1	0	0	0
Heart diseases	0	0	0	0	0	0	0	1	0	0
Lung disease	0	0	0	0	0	0	0	0	1	0
Asthma	0	0	0	0	0	0	0	0	0	1

the model proposed by the article in Nature Medicine contains only part of the symptoms, which is included in the DECODE model. Hence, the first 5 cases contain values only for the common presence of symptoms in the model. The next 5 contain all possible ones and it should be mentioned that the model in the article omits them. In the case of comparative analysis, it has been noted that the DECODE model uses artificial intelligence in its broadest sense and this significantly increases its capabilities. In simplest terms, artificial intelligence (AI) is a system or machine that imitates human intelligence in the performance of tasks and can gradually improve on the basis of the information collected [19, 20]. Artificial intelligence has become a catch-all concept for applications performing complex tasks. The AI is more about the process and possibilities of super-assisted thinking and data analysis than about a specific format or function.

When both models were used, the result was achieved in a numerical form (Table 2). To be able to compare the results unequivocally, the data for the model in the article was multiplied by a hundred to obtain the same row of values. Colors indicate which results predict a positive test result (red) and those which predict a negative test result (green). In the case of the DECODE model, according to the given scale, values above 40 were considered highly likely to pass the test. [13] For the second model, the value exceeding which indicates a positive result is 50. As noted in 9/10 of the cases, both models indicate the same result. The difference is only in case 9, where the DECODE model indicates the probability of a positive result and the article model indicates the probability of a negative result.

Table 2
Comparison of results against both models

	DECODE model result	NATURE model result	Difference
Case 1	44.05	69.21	match
Case 2	14.31	40.61	match
Case 3	44.05	73.30	match
Case 4	14.31	31.43	match
Case 5	44.05	83.34	match
Case 6	34.63	27.49	match
Case 7	19.65	32.30	match
Case 8	44.05	59.15	match
Case 9	**43.69**	**30.36**	**no match**
Case 10	58.02	70.68	match

As a result of the analysis, it was decided to use the prediction model proposed by a research group from the Silesian University of Technology, which calculates the risk of coronavirus infection on the basis of several basic questions. This is due to two reasons. Firstly, the model takes into account more symptoms and additionally takes into account contact with the infected person and the presence of chronic diseases. Secondly, this model is the only case that differs in the results indicating the probability of a positive result. It is considered that it is better to overqualify someone as positive than the opposite as negative. This approach allows for a greater reduction in COVID-19 transmission.

To obtain the result of the prediction, the user must respond or mark his state. Finally, after submitting the data to the API and obtaining a result, he receives a score on a score scale (0–100) and information on whether the system predicts whether it is potentially positive or negative (Fig. 6). The concept is that the user would only be able to complete the survey once a day. And if he did not fill it in two days in a row, he would be informed by means of a notification to complete it. In this way, the system would have the current status of the user on a continuous basis. This would have a positive impact on the contact tracing element. Thanks to the constantly updated information, it would be possible to effectively warn the people with whom the user would be in contact with in public spaces [21].

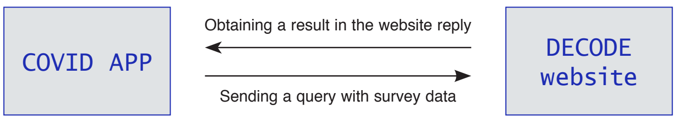

Fig. 6. DECODE website resource usage scheme, system usage

After completing the survey, the user receives information about the result. It predicts whether the user is potentially infected. The results are presented in a clear and legible way. A score is shown, as well as the information based on it, e.g. 'your test result is potentially positive'. In the same view, the user is given the opportunity to move on to a view in which he or she receives concrete and simple recommendations for action to be taken in a given situation [22].

3.3. Contact tracing element

The second main element of the application is a system for tracking contacts between users of the application and tracing whether there has been potential contact with an infected person. Currently, most of the applications in the world that offer the contact tracing function are based on Bluetooth and the "Notification Exposure API", created by the cooperation of Google and Apple. The principle of operation is that the application monitors our environment for other devices on which it is installed. If it finds them and the contact of our phone with the phone of another person will take at least 15 minutes and will occur at a distance of less than 2 meters – it will remember it for 14 days. If during this time the owner of one of the devices falls ill, users of the application with whom he has met will be notified. All this happens completely anonymously. However, when analyzing the actions of such applications, it is easy to come to the conclusion that they have a type of gap in them. What if the user simply lives next to the sick person's flat? Despite the lack of contact, the application will inform about this. Similarly, in situations where users are close to each other while standing in traffic jams or, for example, in the open air, where the risk of infection falls dramatically in relation to closed spaces.

When we look deeper into the situations where the risk of infection is the highest, we see that these are public places such as shops, galleries, places of worship, public transport vehicles, and so on. Wherever many people pass through, many surfaces are touched and, in addition, there is not a sufficiently efficient air circulation and it is even a closed one. In reaching such conclusions, it has been noted that, in this case, it makes no sense to rely on the mere proximity of users, but to rely on their presence in a given public entity. Such as a shop, for example. When considering a situation in which someone enters a shop and touches various items, he or she corrects the mask, continues to touch, deletes purchases, and leaves. Even though he has taken hygiene measures, there is a risk that he has left the virus particles in the places he has touched. It is enough for the next customer to visit the same shop after him or her to touch the items as well and, for example, to improve the mask, which is a common activity among people today. In such a situation, there is a real risk of the virus being transmitted despite the lack of close contact. Therefore, based on our own analysis of the collected facts, we propose the concept of this application element, which would carry out contact tracing, not on the basis of Bluetooth connectivity, but the combined value collected from GPS, Wi-Fi, and cellular network connections. Additionally, a light sensor present in practically every modern smartphone would support it. On the basis of the analysis of the collected values from these sensors, there is a possibility to determine whether a person is inside a building or in an open space. In this way, by analyzing at the same time publicly available data about such places, it would be possible to define whether users have visited the same, e.g., a shop in a short period of time.

The collection of location information from inside buildings only on the basis of a GPS signal is exposed to large errors in the results [23]. Our solution is based on the concept of a project in which, with the help of many smartphone sensors, the authors were able to provide information whether the subjects are inside or outside the building. Specific patterns of behaviour of sensors such as GPS, cellular network signal, light, and magnetic field sensor were noticed depending on the place of measurement – inside the building, near the building, and in the open space [24]. The light detector takes the light sensors to the interception of ambient light signals to determine the environment type. It also uses two other lightweight sensors, a proximity sensor and a system clock to assist detection. Based on the tested pattern and time of day support, a system has been created that points to one of three positions – outside, inside, and near the building [24]. The cellular detector detects the attenuation of cellular signals caused by obstacles (e.g. walls).

This normally indicates the input/output of the device to/from the room environment. As a result of the advanced calculations carried out by the authors of the article, patterns allowing to determine the environment of the device were noticed. They are determined, among others, by the signal strength and the number of cell towers (BTS) connected [24].

The magnetism detector uses dramatic magnetic field disturbances in or near buildings during the movement of a mobile phone. This can distinguish between indoor/semi-outdoor environments and outdoor environments. Many steel structures and electrical equipment interfere with the geomagnetic field and generate electromagnetic fields in the internal environment. Interference with the Earth's magnetic field inside buildings can be used as indicators for indoor location. Based on the patterns observed, they have been adapted to specific environments [24].

In the concept of the application described in the paper, it is proposed to combine this type of detector with an API supporting the exact positioning of the smartphone, such as the Geolocation API from Google [25], which returns a location and accuracy radius based on information about cell towers and WiFi nodes that the mobile client can detect. The combination of accurate location detection with accurate location information will allow the selected contact tracing function to be fulfilled. This will make it possible to determine whether a given user was in a public place and what place it was. The precision of the information obtained could be supported if the system searches the Internet in the background for information about the character of a public place based on the location. The currently available APIs, such as the Place Search API, could also be used for this purpose. It would also be useful to track Wi-Fi connections in public places such as public transport vehicles. Currently, most of them have a free city internet transmitter. Tracking such connections would give measurable information about being in a vehicle, which would be difficult to trace with the help of location functions due to continuous traffic. And in this way we obtain information about a specific vehicle and the time of connection. The ideal solution for drawing conclusions and processing such information is based on machine learning and artificial intelligence, so that, as users and data volumes grow, the precision of prediction and analyses would increase, providing increasingly accurate data.

The application and its systems, when a potential contact is detected, are like visits to the same public place for more than a quarter of an hour and data on how the user has moved and, on the other hand, based on information from user surveys, would warn of potential risks [26]. At the same time, it would offer concrete guidelines for further behaviour. This would not indicate a certain contact but a potential contact. The user would know how to behave in the place where the potential contact was identified and on the podium of the information provided, pay attention to himself, and isolate himself, e.g., until he performs a test or observes his well-being (Fig. 7).

3.4. Utilisation of 5G and Internet of Things (IoT)

While analysing how the user would have to use the application to be as accurate and efficient as possible, it was noticed that a type of openness is required. Awareness that it is tracked using virtually all relevant phone sensors. With the current knowledge of data flow and how it is used, this can be a mental barrier for the user. Additionally, using all these sensors for most of the day would significantly drain the battery of the user's device, which, apart from the operation of the conceptual application, would be used for basic and regular tasks for a person, i.e. calling, browsing the Internet or social media. This puts a big question mark on whether the majority of users would share all this data and whether they would use the application at all. The potential answer to such problems in the future is the 5G technology and the Internet of Things [27], which would allow

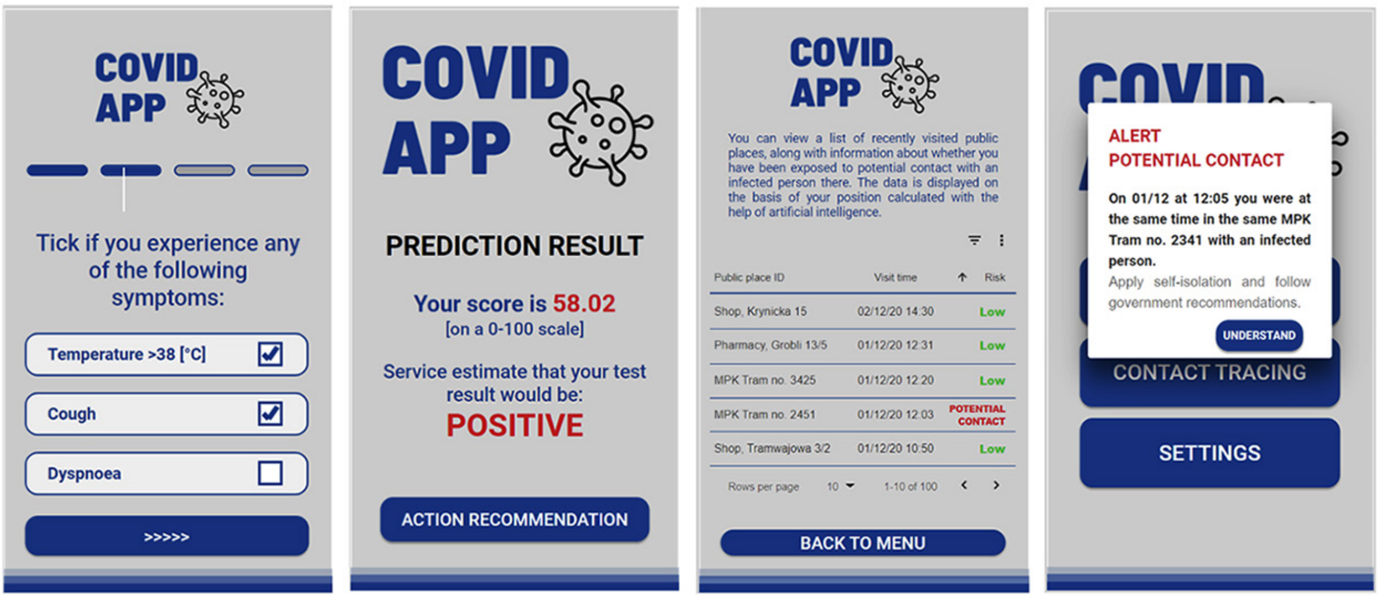

Fig. 7. GUI view of the proposed tool

the user to download the awareness of the shared data and significantly reduce the use of batteries by giving up all sensors except for the connection to the mobile network to which it is connected anyway on a continuous basis. [28, 29] 5G networks have been designed to work with 4G networks, using a range of macrocells, small cellular transmitters, and dedicated in-building systems [30]. Small cellular transmitters are mini base stations designed to build a very local coverage, i.e. usually from several dozen to several hundred metres, providing radio illumination of macrocell networks with a longer range. Small cellular transmitters are crucial for 5G networks also because millimetre frequencies (with millimetre wavelengths) have a very short range. Beam control is a technology that allows Massive MIMO based station antennas to direct radio transmission to specific users and devices instead of scattering it in all directions. This increases efficiency while reducing interference (unwanted radio signals). The advantages of the 5G technology would allow for the revolutionary use of such applications on a scale previously unknown [31]. The need for sensor tracking would be eliminated, as a fully developed network with this technology would allow the tracking of users and their interaction with each other. [32–34] This is an undeniably incredible opportunity for the future and, as such, the concept of this application would be most likely to succeed.

4. CONCLUSIONS AND FUTURE WORK

Despite the implementation of increasingly new measures to combat the global coronavirus pandemic, there is still a large increase in the number of people infected and deaths caused by the disease. Applications that track contacts between people or collect data from them about current symptoms are also part of this fight. The concept of an application as a tool to support the fight against COVID described in the paper is partly based on current solutions. However, thanks to noticing potential issues and gaps, it has been improved. Its advantage is the ability to track contacts collected and analyzed on the basis of presence in public places, which are closed spaces, and not just on the basis of the mere fact of the proximity of the devices, which allows establishing a Bluetooth connection. Collecting information from smartphone sensors to determine whether users are inside or outside the building allows to exclude low-risk situations such as standing in a traffic jam in separate cars or walking in an open air park. A strong element of the concept is to link the tracking of the user with regular questioning of his symptoms and analysis to determine the likelihood of a positive test result. In this way, users are aware and receive concrete tips on how to proceed. They can, for example, isolate themselves until the test is carried out, they are simply more cautious.

The paper provides an extensive review of the current solutions to combat the global pandemic. It proved to be very difficult to obtain reliable and accurate information. This is due to the fact that this is a recent and still not well-known problem. All current studies are in practice in the initial stages. The pandemic lasts for less than a year. It is hard to find comprehensive and strongly supported conclusions in available publications. Despite this, there was also a review of current and used mobile applications and internet tools. This allowed specifying the previously mentioned application assumptions, which were divided into three elements: data processing, infection risk prediction, and contact tracing.

To achieve the best possible results of the prediction using the tool, current scientific research in this area has been analyzed. It allowed for the selection of two for comparative analysis, which allowed for the selection of the most accurate predictive element of the application. In addition, in the case of the contact tracing element implementation, the published scientific research on indoor/outdoor location was based on the available smartphone sensors. Combining these solutions with the capabilities of artificial intelligence algorithms to process substantial amounts of data, analyze the location and the potential state of the user gave promising results.

The potential weaknesses of the concept of an application as a tool to support the fight against a spreading pandemic are also presented. The 5G technology and the capabilities of the Internet of Things are indicated as the most appropriate response to significant development and expansion of capabilities. The soon-to-be-available highly advanced 5G mobile network technology using the current network architecture combined with new radio solutions will eliminate potential problems and raise this solution to an unprecedented level.

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