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The Role of AI in Predicting Infectious Diseases: A Systematic Review of Current Methods and Future Directions

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Abstract:

Objective: This paper presents a review of artificial intelligence (AI) methods in developing a system for predicting the development of infectious diseases in humans, along with the formulation of key principles for the step-by-step implementation of these methods.

Materials and Methods: The study begins with an assessment of the relevance of applying AI techniques and methods to detect infected individuals in various scenarios. This is followed by a systematic review of relevant literature and research in the field of identifying methods to detect conditions in humans that deviate from normal, utilizing search engines such as Google Scholar and PubMed.

Main Findings: Infectious diseases impose a significant burden on individuals in the modern world due to their long-lasting consequences both during and after the illness. Consequently, there is an ongoing need to explore novel methods and approaches for diagnosing infectious diseases at their early stages of development. One of the most promising directions in contemporary medicine is the application of artificial intelligence in the diagnosis and prognosis of infectious diseases. Through the use of machine learning algorithms, AI systems can analyze vast amounts of data and discern patterns that are not easily identifiable through manual examination. This facilitates the early detection of infectious diseases and aids in preventing their spread. The development of an artificial intelligence-based system capable of providing answers regarding the potential infection of specific individuals or groups, as well as the risk of contagion to others, is a highly relevant task. Such a system could employ video recordings and/or photographs from cameras to analyze human movement patterns through machine learning techniques. The development of such a system could be especially beneficial for security organizations and healthcare institutions responsible for public health.

Keywords **—**

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I. INTRODUCTION

Infectious diseases remain a serious problem to this day and have consistently ranked highest in terms of primary morbidity for many years. They cause a significant number of deaths and disrupt the health and well-being of millions of people worldwide. An example of this is the recent COVID-19 pandemic, which has claimed the lives of more than 7 million people worldwide and over 400,000 people in the Russian Federation, according to the World Health Organization [1], and these are only officially confirmed cases. Artificial intelligence systems, particularly object detection methods, can help in early disease detection.

Object detection and recognition remain one of the most fundamental and complex aspects of computer vision and image recognition applications. Thanks to the successful application of deep and convolutional neural networks, especially in recent years, significant progress has been made in various areas of artificial intelligence. This progress includes tasks in computer vision such as classification, segmentation, and object detection. Object detection techniques can play a crucial role in identifying and controlling infectious diseases.

Object detection involves image classification and semantic segmentation. Visual object detection is the process of both image classification and localization. This task becomes more challenging than simple image classification or classification with localization because an image typically contains multiple objects of different categories. Detection involves determining the location of object instances in a given image and assigning each instance the corresponding class label from a wide range of predefined classes [2–5].

The effectiveness of methods for video analytics tasks is assessed using the following classification metrics:

Accuracy: The proportion of all correctly classified objects to the total number of objects.

Sensitivity: Measures the proportion of true positive objects that the model correctly identifies as positive.

Precision: Measures the proportion of true positive objects among the objects identified by the model as positive.

Specificity: Measures the proportion of true negative objects that the model correctly identifies as negative.

F1 Score: A metric that combines precision and sensitivity, representing their harmonic mean. It is used when choosing the best among several artificial intelligence methods or tuning a method because achieving the maximum values of precision or sensitivity simultaneously is not always possible, and a balance between these features needs to be found.

Furthermore, it should be noted that specificity is more important than sensitivity in the diagnosis of diseases at early stages for the purpose of preventing their progression and/or spread. This is because in such cases, the weight of a false-positive result is high. This distinguishes a group of so-called screening methods, where the priority is not to miss an affected individual, while additional testing of a certain number of healthy individuals is not a critical event.

With the advent of deep learning, artificial neural networks have become the most popular approach for object detection research. These networks have demonstrated significant performance in object detection tasks, and there are many different models available for this purpose [6]. For instance, in the article by Abiodun O.I. and colleagues [7], a comprehensive review of artificial neural network (ANN) methods was conducted to identify the most popular models for object detection research. The study analyzed 500 articles related to the application of ANN models. It was shown that recurrent neural networks (RNNs), convolutional neural networks (CNNs), recursive neural networks (RecNNs), multi-layer perceptrons, and single-layer perceptrons are the most commonly used models, with representation percentages of 29.38%, 10.21%, 8.8%, and 7.7%, respectively, among the articles reviewed. These models achieved average accuracies of 83.39%, 83.76%, 89.96%, 83.56%, and 82.54%, respectively. However, it should be noted that this does not necessarily imply that they are the best models, as there are more advanced solutions with improved effectiveness.

Additionally, it should be noted that in the diagnosis of diseases at early stages for the purpose of preventing their progression and/or spread, specificity is more crucial than sensitivity because of the high importance of avoiding false-positive results. This distinction is particularly relevant in screening methods, where the primary goal is not to miss an affected individual, and additional testing of healthy individuals is not critical.

With the emergence of deep learning, artificial neural networks have become the predominant approach for object detection research. These networks have demonstrated significant performance in object detection tasks, with various models available for this purpose [6]. For example, a comprehensive review by Abiodun O.I. and colleagues [7] identified the most popular models for object detection research. The study examined 500 articles related to the application of artificial neural network (ANN) models. It revealed that recurrent neural networks (RNNs), convolutional neural networks (CNNs), recursive neural networks (RecNNs), multi-layer perceptrons, and single-layer perceptrons are the most commonly used models, with representation percentages of 29.38%, 10.21%, 8.8%, 8%, and 7.7%, respectively. These models achieved average accuracies of 83.39%, 83.76%, 89.96%, 83.56%, and 82.54%, respectively. However, it should be noted that this doesn't imply that they are the best models, as there are more advanced solutions with improved performance.

The development of deep learning models has helped improve the accuracy of diagnosing diseases with low intensity, although there was no statistically significant relationship found between accuracy and factors like image resolution, dataset size, AI model architecture, or the number of diseases.

In the study conducted by Jin B. and colleagues [13], the possibility of diagnosing Parkinson's disease (PD) through facial expression recognition was explored. The classification of PD was performed by detecting changes in key facial points in short videos. The diagnostic model for PD was built based on facial expressions. Classification was carried out using traditional machine learning algorithms and recurrent neural networks (RNNs) based on long short-term memory (LSTM) architecture. Videos were divided into individual frames every 0.1 seconds, with a total of 176 recordings, each lasting 5 seconds. After applying LSTM, the model achieved precision and F1-score of 86% and 75%, respectively. The F1-score reached 99% when support vector machines (SVMs) were used for amplitude-based facial expression features and fine muscle group tremor analysis.

The COVID-19 pandemic highlighted the importance of non-pharmaceutical interventions, such as mask-wearing and maintaining social distance, to curb the spread of the virus. Real-time distancing assessment and face mask detection methods were proposed for implementation in public transportation systems during and after the COVID-19 pandemic. However, large-scale image analysis of social media users using deep learning demonstrated that models built on such images with geotags could be a powerful tool for government authorities to track the pandemic's spread but could also raise concerns about invading people's privacy.

In the study by Bose S. and colleagues [16], a method for detecting violations of mask-wearing and the inability to maintain social distance was proposed for reducing the transmission of infectious diseases in various settings, such as streets or stores. A convolutional neural network (CNN) with the YOLOv3 architecture was used to calculate the distance between two people in a specified area and assess the presence of masks. The system achieved high accuracy in determining mask-wearing, with a precision rate of 99.2%.

Hand hygiene monitoring systems have advantages and disadvantages when used to enforce hygiene compliance among people in public places or hospitals. Benefits include increased compliance, improved patient safety, and reduced infection spread. However, drawbacks may include implementation costs, patient privacy concerns, and the potential perception of the system as intrusive.

In the study by Kim M. and colleagues [18], an automated monitoring tool was proposed to enhance hand hygiene control among anesthesiologists using video footage from an operating room. The tool utilized spatiotemporal characteristics with a 3D CNN. An area of interest (the upper body of the anesthesiologist) was defined and processed with a temporal smoothing filter. The system classified two classes: hand rubbing and other movements, achieving an overall accuracy, precision, sensitivity, and F1-score of 76%, 85%, 65%, and 74%, respectively.

Respiratory signals are essential health indicators used as effective biomarkers for detecting respiratory diseases in clinical settings, including lung and heart function, breathing abnormalities, and respiratory infections. For instance, respiratory rate is a vital sign sensitive to various pathological conditions. Therefore, there is a need to continue researching and developing methods for monitoring respiratory signals and detecting respiratory disorders.

Remote Health Screening for Respiratory Conditions: Jiang Z. and colleagues [20] describe a remote intelligent health screening system based on preliminary and auxiliary diagnosis of respiratory diseases using data on a person's respiratory rate. This system combines facial recognition technology with two-camera (color and thermal) visualization to collect data on temperature and respiratory frequency. By analyzing temperature changes around the nostrils during breathing cycles, the system can estimate respiratory frequency. However, the presence of masks can hinder facial feature recognition. To address this issue, the system uses a combination of two types of videos to extract respiratory data. The study achieved a precision rate of 83.69%, sensitivity of 90.23%, and specificity of 76.31%.

Portable Wireless Breathing Monitoring: Zhang C. and colleagues [21] present an intelligent, portable, and wireless breathing monitoring system for real-time assessment of a person's respiratory behavior. The system includes a triboelectric breath sensor, hardware for data collection, preprocessing, and wireless data transmission, machine learning algorithms for improved recognition accuracy, and a mobile terminal application. The triboelectric breath sensor, made using screen printing, is lightweight and biocompatible, providing rapid response to respiratory flow rate. The decision tree model was used for identifying breathing signals with an accuracy of 97.2%.

Cough Acoustics for Disease Detection: Acoustic characteristics of coughs contain vital information about pathological changes in the respiratory system. Detecting cough manifestations and diagnosing diseases based on cough signatures can play a crucial role in the application of AI for predicting respiratory diseases. For example, Chung Y. and colleagues [24] aimed to develop an AI-based pneumonia diagnostic algorithm using cough sounds. They collected cough sounds from adults with pneumonia or other cough-inducing illnesses. The algorithm quantified coughs using loudness and energy, which were used to generate sound levels and spectral variations. The developed algorithm demonstrated a sensitivity of 90.0%, specificity of 78.6%, and an overall accuracy of 84.9% for differentiating between coughs in the pneumonia group and the non-pneumonia group, outperforming the diagnoses made by pulmonologists based solely on cough sounds.

These studies highlight the potential of AI and deep learning in the field of respiratory health monitoring and diagnosis, offering promising solutions for early detection and assessment of respiratory conditions. These technologies can serve as valuable tools for healthcare professionals in improving diagnostic accuracy and patient care.

II. Development of the System

The development of the forecasting system proceeds through several stages, as presented in Figure 2. Each of these stages has its significance and is aimed at creating an effective system that can detect potential diseases at early stages and prevent their progression and/or spread. The emergence of explainable artificial intelligence is driven by the complexity of understanding the principles of operation and interpreting the results of complex machine learning methods, such as neural networks. The gap between AI models and human understanding is known as the "black box" transparency [25]. For this reason, developers are focused on simplifying AI models to improve clinicians' confidence in using them [26]. In the work of Kasianenko K.V. et al. [27], a methodology for building a decision support system for predicting the severity of infection caused by SARS-CoV-2 in young individuals is described in detail and step by step. The architecture of the fully connected neural network achieved the following metrics for the validation dataset: accuracy - 92%, sensitivity - 91%, and specificity - 74%. The described methodology can serve as a guide for the development of a forecasting system. In healthcare, where decision-making is based on the assessment of medical data and disease prediction, this can lead to significant challenges. For example, if a system predicts a diagnosis or suggests appropriate treatment but cannot explain its findings, it may lead to distrust among healthcare professionals. To increase trust in AI models, it is proposed to include seven requirements in their development: human factor and supervision, technical reliability and security, data confidentiality and control, transparency, diversity, impartiality, social and environmental well-being, accountability [28]. The development of explainable AI in medicine holds significant promise. For instance, creating more accurate disease forecasting models can increase the precision of diagnosis and prevent inadequately justified forecasted outcomes. Additionally, explainable AI can reduce the cost of medical services, expedite diagnosis, and decrease the risk of errors during physician diagnosis. Ultimately, the development of explainable AI will accelerate the implementation of data-driven analytical solutions to improve patient care [29]. It should be noted that the development and use of AI must be accompanied by a responsible approach to its application and adhere to patient data confidentiality and protection. Furthermore, the responsibility for decisions made based on AI predictions should lie with healthcare professionals who should take them into consideration when making final decisions. In the Russian Federation, the process of implementation...

The implementation of AI solutions in the healthcare system is in its initial stages, so there are several aspects that need to be considered during its implementation [30]. One aspect is the strict regulation of AI deployment to ensure transparency in its operation and the ability to explain the decisions it makes, as AI is increasingly affecting the results of diagnosis and treatment. Regulation will help increase trust in AI systems among healthcare professionals.

Another aspect is the training of healthcare professionals to interact with AI systems and the integration of these systems into existing medical practices, which will require significant efforts in training and preparing personnel, as well as aligning new methods and standards with healthcare organizations. Despite the challenges mentioned above, the implementation of such a solution will lead to faster patient diagnosis.

It is also important to ensure high-quality and accurate data that AI systems rely on, which will require the application of standards for collecting, storing, and processing medical data collected from patients. To achieve this, elements of gamification can be introduced for patients to create a sense of "play" when providing medical data, and high-resolution cameras may be required as part of this work. Additionally, it is necessary to comply with the legal requirements for the protection of patients' personal data [31].

For the successful application of AI in predicting the development of infectious diseases, the following clear and structured implementation scheme is provided:

Use image segmentation to analyze video frame by frame. Determine a person's breathing, body temperature, the presence or absence of a mask, body position relative to others, posture, and so on. It should be noted that the creation of a feature set for evaluation that combines accessibility for video capture and informativeness is a separate stage of preliminary analysis.

The size of the video recording is limited to the characteristic that needs to be determined for the patient. For example, to determine breathing, the video clip should be at least a few seconds long and have a sampling rate of 10 Hz, while for determining temperature or body posture, a single frame may be sufficient. Long recordings will be excessive as they would burden the neural network. The most common division of the dataset into training, testing, and validation parts is 60%, 20%, and 20%, or 70%, 15%, and 15%.

For person identification in the video, SVDNet can be used, and for calculating the distance between people, YOLO can be employed. These are neural networks that perform automatic labeling and are trained on large and well-annotated databases, such as COCO. The labeling should be verified by a specialist.

Cross-validation can be performed by adding the appropriate parameter during the construction of the neural network in Python using the TensorFlow package, which also allows obtaining classification metrics such as accuracy, sensitivity, and specificity.

The training and testing process will involve several stages. First, the most promising method for analyzing video and extracting motor patterns needs to be selected. Then, the video sequence should be labeled for the chosen methods and the quality of labeling for motor patterns related to early stages of infectious diseases should be checked. Next, cross-validation of methods using specified quality metrics should be performed to select the best method and determine its optimal hyperparameters. After that, the training of the selected method on the training dataset begins, following the steps described above. Upon completion of training, testing on the testing dataset is conducted to evaluate the effectiveness of the method.

If the test results are satisfactory and the system meets the performance characteristics for deployment in a healthcare organization, a lengthy stage of technical and operational documentation development begins. This documentation will contain a complete description of the system, usage procedures, as well as instructions for data processing and storage. The documentation should be designed for healthcare personnel who do not have a technical background and should be available in electronic form. User training should include both theoretical knowledge of how the system works and how to interpret its outputs, as well as practical exercises on real examples.

Online courses, as well as in-class instructors, are used for medical staff training. Once the medical personnel acquire the necessary skills, procedures for using the system in the healthcare organization are determined. This may include defining which patients will be examined using the system, how often, and in what form the system's results will be documented in medical records. Additionally, it is essential to develop a policy regarding responsibility for system errors. It is necessary to identify who will be held responsible for errors that may occur as a result of system usage. Furthermore, the causes of errors should be investigated, and corresponding changes in system usage procedures should be made to prevent errors in the future.

It is important not to forget the limitations of using a forecasting system in the medical field, namely:

The ability to detect only acute respiratory viral infections (ARVI) and only in the early stages. It is not possible to register ARVI in the advanced stage due to false positives for other diseases with similar motor patterns, of which there may be many.

The inconvenience for falsely identified patients as being ill. These individuals will need to spend time and effort to recheck the result, meaning they would have to visit a doctor for diagnosis and undergo further examination.

After identifying an infected person, reexamination by a doctor with subsequent clinical and instrumental diagnostics is required, which can incur significant additional costs for both the medical institution and the state as a whole.

When working with neural networks for object detection, there is a risk of compromising data confidentiality. The use of networks complicates the identification of the data source for classification, but at the same time, the confidentiality of machine learning systems can be violated as a result of attacks by malicious actors trying to extract patient information or information about the model.

AI-based models have a significant advantage - the ability to train the algorithm without balancing the available training data, even if it is highly unbalanced. To achieve this, an additional method such as anomaly detection in the dataset can be used. The scheme in Figure 3 illustrates this.

Under undeniable signs (US) of ARVI in the scheme, the number of cases of coughing/sneezing per minute and other similar signs is implied, with N being the threshold value. Elevated body temperature above normative values can also be classified as undeniable signs. In general, the set of such signs can be determined based on the results of research on the population of ARVI patients as well as working with experts. Face profile recognition is carried out for individual parts of the face with the assignment of an ID number to each patient. The risk percentage of ARVI after face profile classification and the percentage of anomalies must exceed the corresponding threshold values set based on machine learning model validation results

III. CONCLUSIONS

The best means for developing the proposed system is a neural network, specifically its subtypes - convolutional and recurrent with possible modifications. The system for disease detection can be used to identify potentially infected individuals if they have had contact with a "patient zero," if their facial expressions have changed due to illness (with possible identification of not only infectious diseases), if the population is not following social distancing and hygiene practices, and if they experience difficulty breathing and/or coughing.

The most popular effectiveness metric for the previously discussed methods is accuracy, followed by sensitivity and specificity, which together provide a comprehensive view of the system's performance. A scheme for developing a potential system has been proposed, along with conclusions about its limitations.

distribution.

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