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# HAND MOVEMENT DISORDERS TRACKING BY SMARTPHONE BASED ON COMPUTER VISION METHODS

**Marko Andrushchenko[1], Karina Selivanova[1], Oleg Avrunin[1], Dmytro Palii[2], Sergii Tymchyk[3], Dana Turlykozhayeva[4]**

[1]Kharkiv National University of Radio Electronics, Department of Biomedical Engineering, Kharkiv, Ukraine, [2]National Pirogov Memorial Medical University, Vinnytsya, Ukraine, [3]Vinnytsia National Technical University, Vinnytsia, Ukraine, [4]Al-Farabi Kazakh National University, Scientific Research Institute of Experimental and Theoretical Physics, Almaty, Kazakhstan

***Abstract.*** *This article describes the development of a cost-effective, efficient, and accessible solution for diagnosing hand movement disorders using smartphone-based computer vision technologies. It highlights the idea of using ToF camera data combined with RG data and machine learning algorithms to accurately recognize limbs and movements, which overcomes the limitations of traditional motion recognition methods, improving rehabilitation and reducing the high cost of professional medical equipment. Using the ubiquity of smartphones and advanced computational methods, the study offers a new approach to improving the quality and accessibility of diagnosis of movement disorders, offering a promising direction for future research and application in clinical practice.*

**Keywords**: healthcare, information medical technologies, image analysis, computer vision, artificial intelligence, motion disorders

## ŚLEDZENIE ZABURZEŃ RUCHU DŁONI ZA POMOCĄ SMARTFONA W OPARCIU O METODY WIZJI KOMPUTEROWEJ

***Streszczenie.*** *W niniejszym artykule opisano opracowanie opłacalnego, wydajnego i dostępnego rozwiązania do diagnozowania zaburzeń ruchu ręki przy użyciu technologii wizyjnych opartych na smartfonach. Podkreślono w nim ideę wykorzystania danych z kamery ToF w połączeniu z danymi RG i algorytmami uczenia maszynowego do dokładnego rozpoznawania kończyn i ruchów, co przezwycięża ograniczenia tradycyjnych metod rozpoznawania ruchu, poprawiając rehabilitację i zmniejszając wysokie koszty profesjonalnego sprzętu medycznego. Wykorzystując wszechobecność smartfonów i zaawansowane metody obliczeniowe, badanie oferuje nowe podejście do poprawy jakości i dostępności diagnostyki zaburzeń ruchu, oferując obiecujący kierunek przyszłych badań i zastosowań w praktyce klinicznej.*

**Słowa kluczowe**: opieka zdrowotna, informatyczne technologie medyczne, analiza obrazu, wizja komputerowa, sztuczna inteligencja, zaburzenia ruchu

## Introduction

Existing research represents that kinematic analysis of human movements is critical in rehabilitation research and clinical practice to assess motor function in people with motor system disorders caused by neurological or musculoskeletal disorders. The development of markerless motion capture systems, such as systems based on 3D depth cameras, including technologies such as Kinect, allows us to assess joint kinematics without the rather poor quality of information perception at the level of marker systems, which are the benchmark for such tasks [10].

Given the comprehensive development of artificial intelligence systems, namely machine learning methods and the gradual increase in the computing capabilities of smartphones [5, 9], and in particular their specialized processors for performing tasks related to artificial intelligence, new horizons are opening up for the development of this area and the implementation of more compact solutions that would not require additional equipment other than that available to almost every person with access to the Internet [9, 26].

Modern methods of rehabilitation after upper extremity injuries are quite long in terms of time and often require the supervision of a rehabilitation therapist to monitor the correctness of the exercises. Artificial intelligence automates diagnostic process, reducing the burden on both the doctor and the patient by reducing the time required to supervise the patient [5, 27].

One of the disadvantages of professional medical equipment for the diagnosis of upper limb disorders is its cost and, as a result, its limited availability, which automatically makes it inaccessible to most countries where public funding for medicine is low.

Thus, the question arises of developing a cheap, affordable, fast and effective solution that could at least partially address the above problems.

## 1. Materials and methods

The purpose of this paper is to analyze and present the shortcomings of the means of diagnosing motor disorders of the upper extremities based on computer vision technologies. The TrueDepth camera [24] will be used as the target technology for the study. The advantage of this method is that the camera is included by default in every Apple phone or tablet since 2017, except for the SE series. This solves the problem of accessibility of this method for a very wide category of users. In addition, this technology will improve the accuracy of object recognition in space by providing additional data on their shape and distance.

The TrueDepth camera includes several components that work together to capture 3D information. It uses a dot projector to project more than 30,000 invisible dots onto an object, thereby collecting extensive visual information. This system is capable of recording depth and capturing accurate data in three-dimensional space.

A typical structure of this camera looks like the one shown in Fig. 1. The array of sensors and cameras is located on top of the smartphone in the so-called "Notch" or "Dynamic Island", and at a minimum it includes the following components:

- 12-megapixel camera: A 12-megapixel camera with a $f/2.2$ aperture for taking photos and videos.
- Point Projector: Projects points into space to create a detailed 3D map.
- Infrared camera: captures the points projected by the point projector for 3D mapping, with a resolution of 7 to 12 megapixels depending on the model.
- Flood Illuminator: adds infrared light to improve the system's visibility and accuracy in low-light conditions.

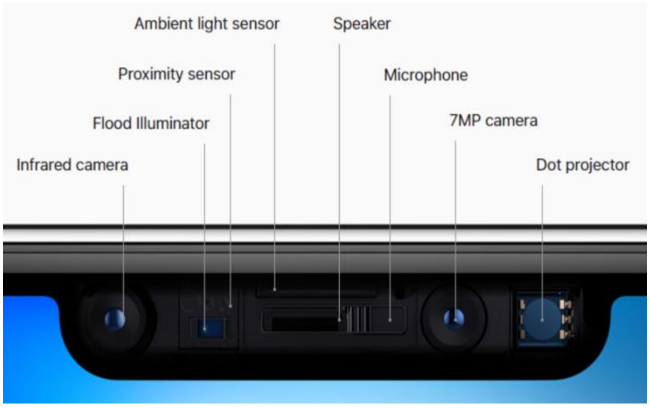


*Fig. 1. The typical structure of TrueDepth*

This camera is able to capture information in a three-dimensional format with high quality and accuracy, so accurate that it can be used to recognize the user's face and further control access to the device and to sensitive user data.

It is relevant that Apple did not make its technology closed [2] to third-party users, so it was the basis for many scientific developments that are somehow related to medicine.

This technology allows you to receive information in the RGBD format [14, 21] (Read Green Blue Depth), which means that in addition to color data, each pixel also records its depth (distance from the camera) in three-dimensional space. Fig. 2 shows the view of the resulting image in RGBD format. On the left is color information (RGB), on the right is information in the form of a depth map [3, 4] of the image. A detailed image of the hand is shown in Fig. 3.

*Fig. 2. RGBD image (color information on the left, depth information on the right)*

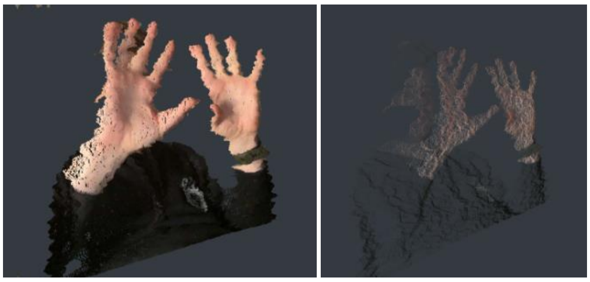

*Fig. 3. A cloud of points with upper limbs*

*Fig. 4. Point cloud with RGB data*

Apple has an open API [15] to access the full functionality of TrueDepth, so development can be significantly accelerated by using an existing testing platform [12].

Thus, the next problem to be solved is the recognition of the hand (hand, fingers and their position in space) in real time on a mobile device. This task can be conveniently divided into several stages:

- search for the hand;
- search for key points of the hand.

The software tool will work not only on devices equipped with TrueDepth technology, so you need to consider the case when hand recognition will take place in a 2D environment.

The need for additional 3D data arises when there is a situation in which it is impossible or problematic to clearly define the target area of the hand or when it is impossible to unambiguously determine the location of hand landmarks that are partially in the camera's field of view or overlapped with other hand objects. In addition, additional 3D data helps in low light conditions or when there is a high amount of background noise in a 2D image, as the quality of detection decreases in such conditions.

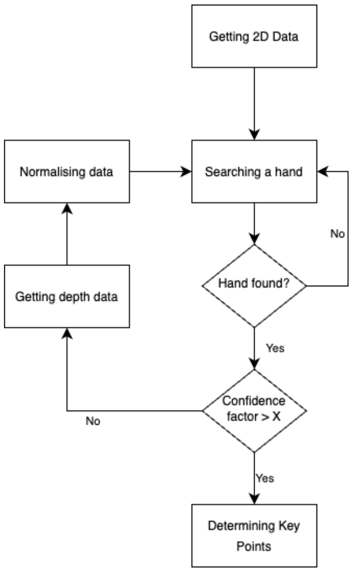


*Fig. 5. General block diagram of the algorithm for recognizing key points of the hand*

Returning to the problem of implementing the function of searching for key points of the hand, this task is quite typical and currently one of the best solutions for 2D data, if not better, is MediaPipe Hands [11].

## 2. MediaPipe hands

This project implements the search for key points of the hand in 2D data. The use of this solution is due to cases when the smartphone is not equipped with a TrueDepth camera.

This solution includes a modified SSD (Single Shot Multibox Detector) [8, 16] neural network for hand detection, a modified FPN neural network [17, 27], and a regression model that determines 21 key points of the hand, shown in Fig. 6. This approach is a standard in the field of hand landmark recognition and provides enough information for its further use in fine motor skills tests, so use this approach in the further development of the neural network for hand landmark detection.

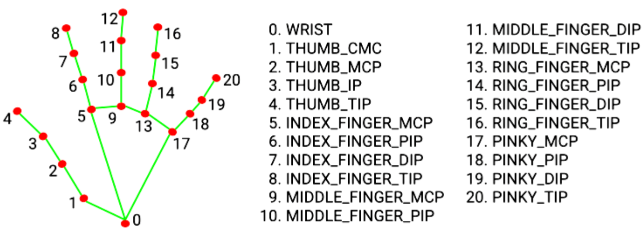


*Fig. 6. Location of key points of the hand [15]*

This solution has the following flowchart, is shown in Fig. 7.

From the flowchart, hand recognition does not take place every frame, but only when the palm changes location relative to the hand landmarks of the previous frame, which gives a strong increase in execution speed by reducing the number of required operations, which is especially important for working with limited mobile graphics card resources.

The input information is an RGB stream of frames, and the output information is 21 3D coordinates of the key points of the hand, the probability of finding the hand in the frame, and the left or right hand marker.

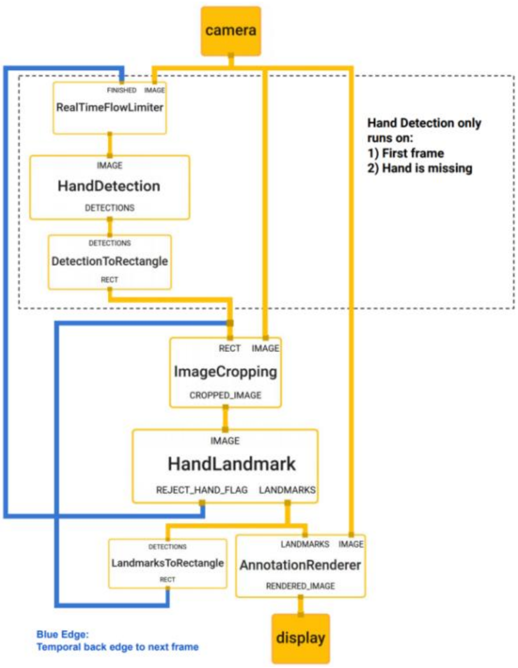


*Fig. 7. MediaPipe Hands block diagram*

One of the important and key features is that it was developed and adapted for use on mobile devices; a comparative table of performance is given below [1, 7, 25].

*Table 1. Comparison of performance of models for finding key points of the hand*

| Model | Params (M) | MSE | Time(ms) Pixel 3 | Time (ms) Samsung S20 | Time (ms) iPhone 11 |
|---|---|---|---|---|---|
| Light | 1 | 11.83 | 6.6 | 5.6 | 1.1 |
| Full | 1.98 | 10.05 | 16.1 | 11.1 | 5.3 |
| Heavy | 4.02 | 9.817 | 36.9 | 25.8 | 7.5 |

Given this data and the characteristics of modern smartphones, its make assumptions about the execution of a neural network on modern smartphones. For this purpose use data on the GPUs of smartphones, since the main work is executed on them.

The Samsung Galaxy S20 (2020) has an Adreno 650 graphics card, with a floating-point performance speed (gflop/s) of 1202.1 (fp32). It is this model that is shown in the table, its newer model Samsung Galaxy S23 (2023) already has an Adreno 740 graphics card with the following characteristics of data execution speed (gflops/s) - 3481.6 (fp32) [13, 22].

*Table 2. Table comparing the computing capabilities of the Adreno 650 and Adreno 740 GPUs*

| GPU | fp32 (GFLOPS) |
|---|---|
| Adreno 650 | 1202.1 |
| Adreno 740 | 3481.6 |
| Difference | +2 279.5 (2.89) |

Given the data obtained, its assume that the speed of BlazePalm will also be 2.89 times faster than on an older generation device.

The Pixel 3 (2018) smartphone is equipped with an Adreno 630 GPU with a floating-point performance rate of 727 (fp32) gflop/s, while the Pixel 8 (2023) [17] has a Mali-G715 MP7 with a capacity of 2415.8 (fp32) gflop/s.

*Table 3. Table comparing the computing capabilities of the Adreno 630 and Immortalis-G715s MC10 GPUs*

| GPU | fp32 (GFLOPS) |
|---|---|
| Adreno 630 | 727 |
| Mali-G715 MP7 | 2415.8 |
| Difference | +1 688,8 (3.32) |

The table represents that the increase in power has been 3.3 times in 5 years.

The Apple iPhone 11 (2017) smartphone is equipped with a built-in Apple A13 Bionic GPU, the speed of floating point operations (gflop/s) is 629.8 (fp32), while the Apple iPhone 15 (2023) with Apple A16 Bionic GPU is 1789.4 (fp32).

*Table 4. Table comparing the computing capabilities of the A13 Bionic and A16 Bionic GPUs*

| GPU | fp32 (GFLOPS) |
|---|---|
| A13 Bionic | 629.8 |
| A16 Bionic | 1789.4 |
| Difference | +1 159.6 (2,84) |

The table shows that the increase in power over 6 years was more than 3 times, which in practice should theoretically speed up the operation of neural networks by 3 times.

Coming back to MediaPipe Hands, its use is conditioned by those cases when 3D data is not available.

To test the operation of this technology, its compile the source code of the application using Xcode (Fig. 8), which is available in the MediaPipe model example repository [27].

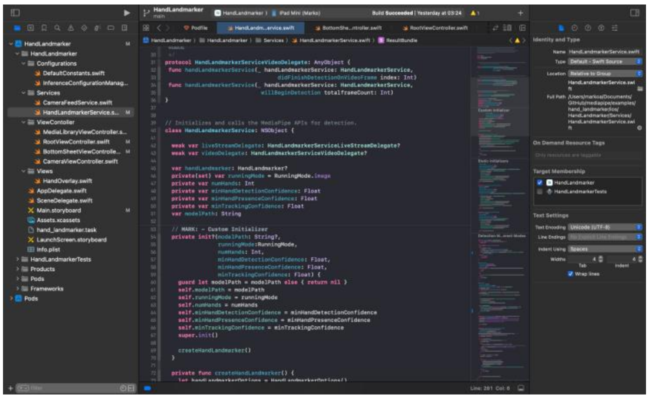

*Fig. 8. Xcode*

In the demo version, implementation of the ability to collect performance data for further analysis by saving it in json format, which will contain a list of measurements containing two types of data InferenceTime in milliseconds of the model and timestamp at which the delay was obtained.

During the testing of this model, a peculiarity was noticed that inferenceTime slowly increased over time, and only in some modes. To evaluate this factor, tests were conducted on three devices: iPhone 13, iPhone SE and iPad Mini 6 generation. These devices are united by the fact that they use almost the same CPU and GPU of the same generation and that they belong to the lowest price point among the entire Apple product line.

For the measurements, it was decided to test for 295 seconds, since after this period, the stability of the application dropped significantly, which indicated the quality of the results obtained.

As part of the preliminary data processing, it was decided to recalculate the timestamp, which contained the number of milliseconds since the beginning of the UNIX era (Jan 1, 1970), by presenting it in the format of time since the beginning of the test.

After that, it was decided to rebuild the dataset by determining the minimum, maximum, and average inference Time values within each second of the test, while filtering out outliers in the data. This was applied by using the interquartile range (IQR) method according to the following formula:

$$D' = \{x \in D |\, LB \leq x \leq UB\}$$

where: $D'$ is the dataset after removing outliers, $D$ is original dataset, $Q1$ is the 25th percentile of $D$, $Q3$ is the 75th percentile of D,

$IQR = Q3 - Q1$,

$LB = Q1 - 1.5 \times IQR$,

$UB = Q3 + 1.5 \times IQR$.

## 2.1. Multisensory hand keypoints detection

There are few studies on this topic, as multisensory object detection is mainly focused on improving the quality of AI for vehicle autopilots, and because the topic of hand keypoints detection is quite specific. However, these studies describe quite useful methods for detecting objects in multisensory data, which can be used for hand recognition tasks.

A scientific article [13] describes the architecture of the **ContFuse** neural network that uses LiDAR and RGB camera data to detect objects. First, RGB data is processed and then combined with a feature map obtained from LiDAR, after which the final object detection is executed.

Another study [14] describes the architecture of an **MMF** neural network that also uses RGB and LiDAR data. It describes a somewhat more complex approach to feature fusion, namely the use of two separate fusion layers – Point-wise feature fusion and ROI-wise feature fusion.

It should be noted that TrueDepth technology is based on a ToF camera, unlike LiDAR, on which the research is based.

TrueDepth uses a VCSEL laser, and is functionally designed to obtain fairly detailed information about objects in the vicinity (up to 2m), while LiDAR allows for much more accurate and detailed information even at a great distance. Despite this, the final result of both technologies is a cloud of points that differ in density and distance. And this creates the necessary conditions for implementation on a mobile platform, since the fact that TrueDepth data is significantly smaller than LiDAR data, which speeds up the entire processing cycle.

In contrast to the above detection methods, the specificity of object detection on a mobile platform is precisely the strong resource limitation compared to others, so the approach we propose is that the use of 3D data should be only when the confidence factor in hand recognition is lower than that required for further accurate search of key points of the hand. In the above proposed neural network architectures, the rather heavy processes of feature map search and fusion occur continuously on both 2D and 3D data, which has a significant impact on their performance.

## 2.2. Flutter

This framework allows the application to be implemented on the key platforms for this study. To run on different platforms, the application is compiled into native code for each platform, which allows you to get identical performance and access to platform functionality at a level that is identical to native applications developed for each platform separately.

As part of the research, we need the native features of each platform, for Android we need to use the NPU, GPU and RGB camera of the smartphone, for IOS we need NPU, GPU, TrueDepth camera, RGB camera. This problem is solved by implementing plugins for the Flutter framework.

# 3. Experimental results

After testing, the data on the performance of the MediaPipe HandLandmark Detection model was obtained. Several tests were conducted for each device, for each of the model's operating modes. The results are divided into three categories:

- One-hand detection mode with one hand in the frame.
- Two-hand detection mode with one hand in the frame.
- Two-hand detection mode with two hands in the frame.

For the iPhone 13: Fig. 9–11.
For the iPhone SE (2022): Fig. 12–14.
For the iPad Mini 6 generation: Fig. 15–17.
For clarity, was compared these results between devices: Fig. 18–20.

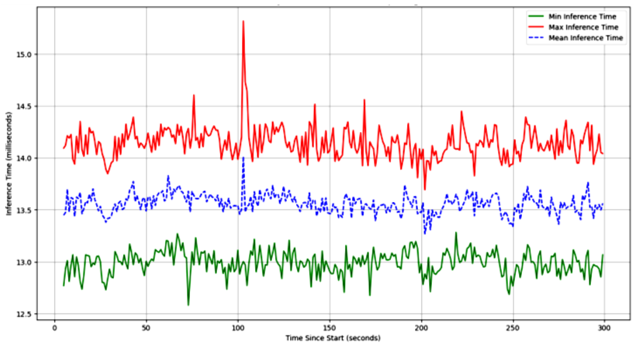


*Fig. 9. Single hand key points detection on IPhone 13*

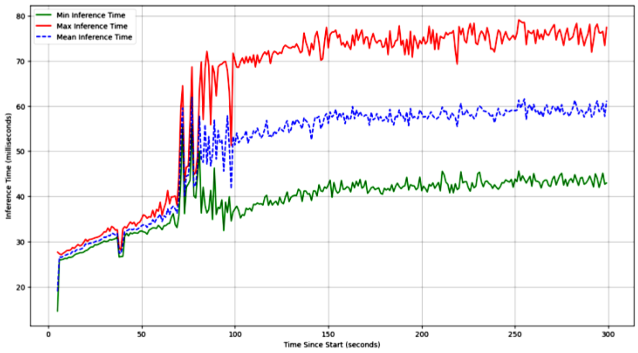


*Fig. 10. Single hand keypoints detection on IPhone 13 multihand mode*

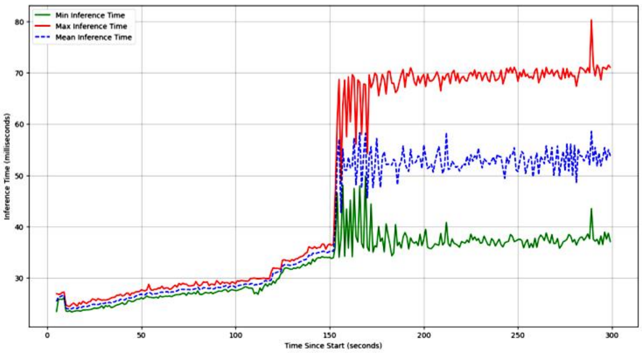


*Fig. 11. 2 hands keypoints detection on IPhone 13 multihand mode*

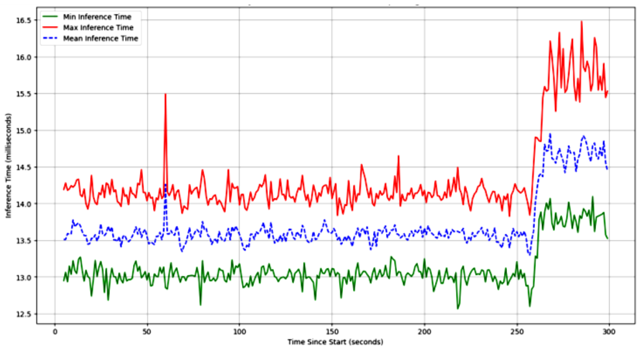


*Fig. 12. Single hand keypoints detection on IPhone SE singlehand mode*

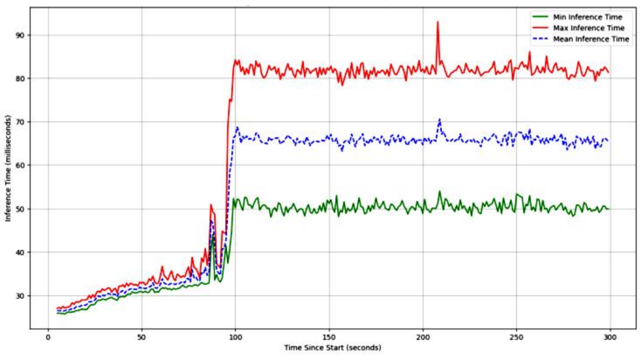


*Fig. 13. Single hand keypoints detection on IPhone SE multihand mode*

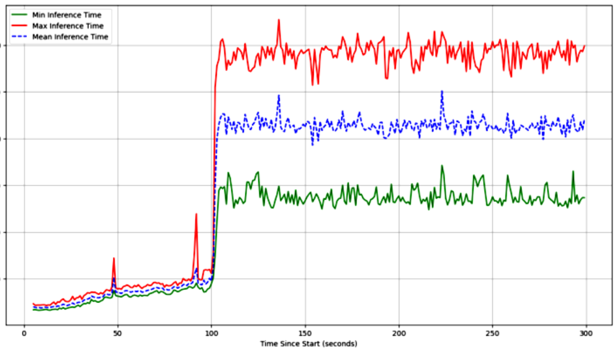


*Fig. 14. 2 hands keypoint detection on IPhone SE in multihand mode*

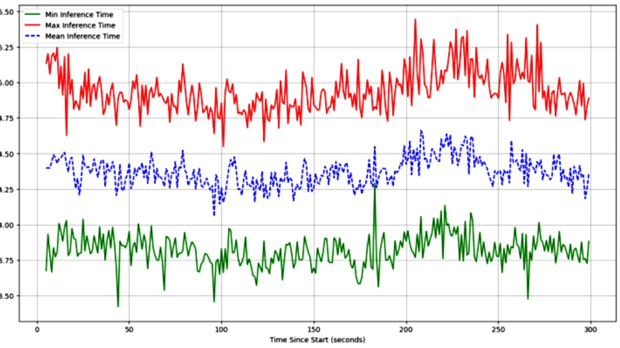


*Fig. 15. Single hand keypoint detection on IPad Mini in singlehand mode*

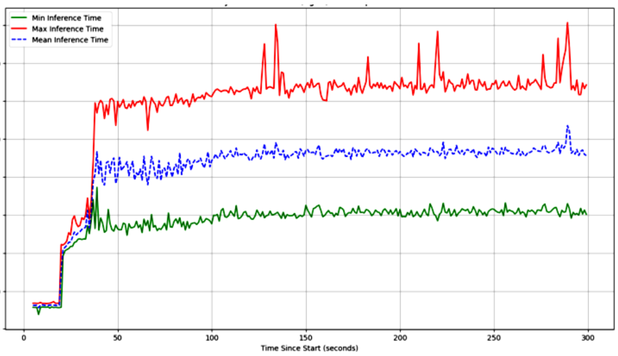


*Fig. 16. Single hand keypoint detection on IPad Mini in multihand mode*

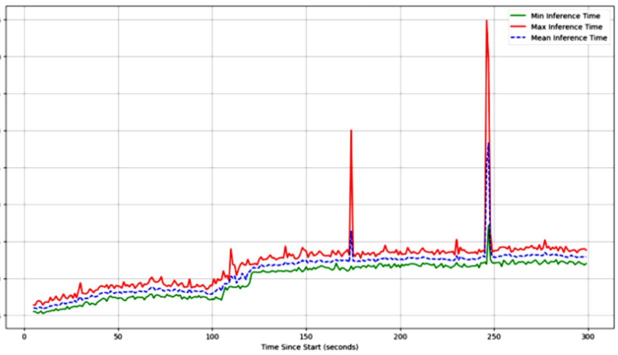


*Fig. 17. 2 hands keypoint detection on IPad Mini in multihand mode*

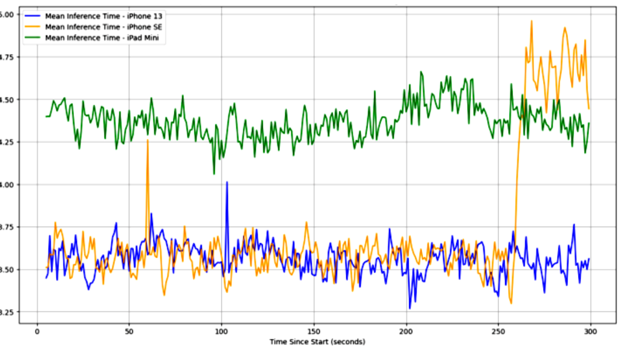


*Fig. 18. Inference time comparison, single hand*

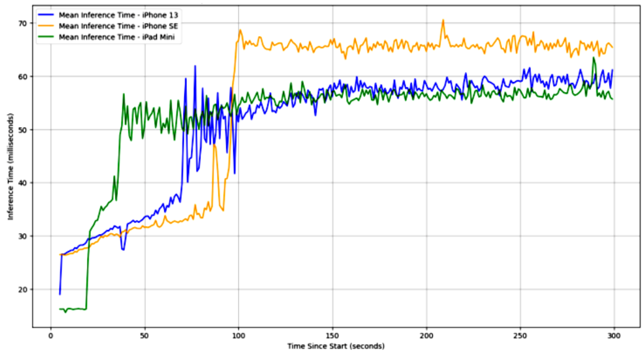


*Fig. 19. Inference time comparison, multihand mode, 1 hand*

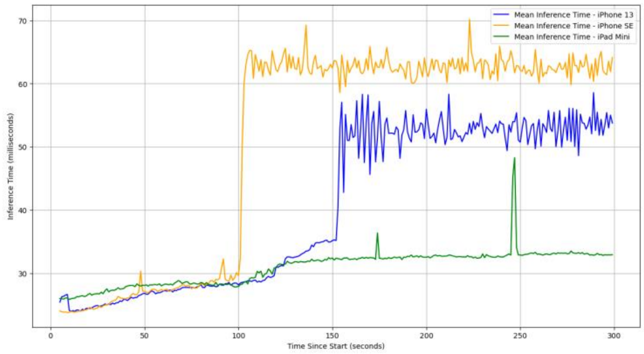


*Fig. 20. Inference time comparison, multihand mode, 2 hands*

Fig. 20 represents the impossibility of the model to work in the mode of detecting key points of both hands, as can be seen from the graph, in fact, only the iPad Mini can work without jumps in the model's latency. This may be due to several factors, the main one is the larger body area compared to smartphones, which contributes to rapid heat dissipation. Therefore, as a result, smaller smartphones can see a huge jump in performance. The iPhone SE has the smallest body of all the devices tested, and although it has identical GPU and CPU characteristics to the iPhone 13, it either starts to lower frequencies first or reduces them more than other devices used in the test.

## 4. Conclusions

The article discusses the prospects for the use of technological tools for the diagnosis of upper extremity motor disorders. The article shows the need to develop a more affordable and cost-effective tool based on existing smartphones [18,19,23]. For this purpose, it is proposed to use machine vision technologies on smartphones. The research presents the need to develop a model for high-quality recognition of limbs and their movements for further analysis of the data obtained by doctors. To improve the quality of pattern recognition on mobile devices, it is proposed to use volumetric data from the ToF camera of Apple smartphones.

The research presents the concept of a neural network model for using these capabilities, which would theoretically allow maintaining a balance between speed and quality of pattern recognition in conditions where the performance of classical recognition methods is limited by poor quality of the original data. To implement this model, we propose to use the techniques used in object detection for self-driving vehicles. These techniques are proposed to be significantly reworked to optimize their computational complexity and adapt them to the type of data obtained from a mobile ToF camera [19,20,23]. This approach will be very relevant and useful when used in telemedicine services [6, 20].

As a confirmation of the idea, was measured the performance of the considered model for detecting key points on three different devices with identical CPU and GPU, in three different modes. For this purpose, graphs of the dependence of the delay on the algorithm's operation time are presented to illustrate these differences.

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**M.Sc. Marko Andrushchenko**
e-mail: marko.andrushchenko@nure.ua

Ph.D. student of the Department of Biomedical Engineering, Kharkiv National University of Radio Electronics, Ukraine. Master's degree in Biomedical Engineering, Bachelor's degree in Software Engineering. Mobile Application Developer

https://orcid.org/0000-0003-1722-2390

**Ph.D. Karina Selivanova**
e-mail: karina.selivanova@nure.ua

Ph.D., associate professor of the Department of Biomedical Engineering, Kharkiv National University of Radio Electronics, Ukraine.
Research interests: rehabilitation engineering, methods of automated processing and analysis of biomedical images, study of individual characteristics of fine motor skills of hands and psychomotor skills, development of tests, complexes for psychoneurology, virtual simulators. Participation in the international project DAAD, (OER) (Hannover, Germany).

https://orcid.org/0000-0003-1002-0761

**Prof. Oleg Avrunin**
e-mail: oleh.avrunin@nure.ua

Doctor of Technical Sciences, professor, Head of Biomedical Engineering Department, Kharkiv National University of Radio Electronics, Ukraine. Scientific supervisor of research work on research of theoretical and technical principles of diagnostics, assessment and correction of medical and social human conditions. Invited Professor in Gottfried Wilhelm Leibniz Universität Hannover (Germany) and Harbin Engineering University (China).

https://orcid.org/0000-0002-6312-687X

**Ph.D. Dmytro Palii**
e-mail: dimapaliy@gmail.com

Head of the Department of Epidemiology, associate professor, doctor of medicine, National Pirogov Memorial Medical University, Vinnytsya.
Research interests: Epidemiology and principles of evidence-based medicine, Communicable Diseases.

https://orcid.org/0000-0001-6537-6912

**Ph.D. Sergii Tymchyk**
e-mail: tymchyksv@ukr.net

Dean of of Information Electronic Systems, associate professor of Biomedical Engineering and Optic-Electronic Systems, Vinnytsia National Technical University.
Research interests: rehabilitation engineering, methods of automated processing and analysis of biomedical images.

https://orcid.org/0000-0003-2977-1602

**M.Sc. Dana Turlykozhayeva**
e-mail: Dana.Turlykozhayeva@kaznu.kz

Scientific researcher, Al-Farabi Kazakh National University · Scientific Research Institute of Experimental and Theoretical Physics, Almaty, Kazakhstan.
Research interests: Experimental and Theoretical Physics, information technologies.

https://orcid.org/0000-0002-7326-9196