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STREAMING MICROSCOPIC IMAGE DATA TO THE CLOUD STORAGE FOR DETECTION OF ACUTE LYMPHOBLASTIC LEUKEMIA USING CNN

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Abstract. *In the modern world, the problem of the prevalence of cancer remains quite widespread, including acute lymphoblastic leukemia. It is very important to diagnose such diseases in the early stages in order to prescribe timely treatment and achieve patient remission. However, the problem that remains to this day is that the diagnosis of the disease based on microscopic images of a human blood smear are manual. This method of diagnosis is prone to errors due to many factors, due to inattention, absence of a specialist in the locality, etc. Therefore, the need for automated data collection of microscope images and their analysis with high accuracy is urgent. Research into the creation of low-cost devices and the creation of neural network architectures that can control the process of analysis and disease detection. It is proposed to develop a network consisting of hardware and software capable of transferring acquired data from the microscope to cloud storage for further use by a convolutional neural network to classify human blood smear images to detect healthy or blast blood cells. A hardware and software complex has been developed for collecting and transferring values from the microscope to cloud storage. The main module for receiving and transferring data to the cloud is a Raspberry Pi single-board computer that works on Wi-Fi technology. In conclusion, the proposed system is capable of ensuring the effectiveness of diagnosing blood cancers not only of lymphoblastic leukemia, but also of other types.*

Анотація: *У сучасному світі досить поширеною залишається проблема онкологічних захворювань, у тому числі гострого лімфобластного лейкозу. Дуже важливо діагностувати подібні захворювання на ранніх стадіях, щоб вчасно призначити лікування і досягти ремісії пацієнта. Однак проблема, яка залишається донині, полягає в тому, що діагностика захворювання на основі мікроскопічних зображень мазка крові людини проводиться вручну. Цей метод діагностики схильний до помилок через багато факторів, а саме неуважність спеціаліста, його відсутність в місцевості тощо. Тому актуальною є необхідність автоматизованого збору даних мікроскопічних зображень та їх аналізу з високою точністю. Дослідження створення недорогих пристроїв і розробки архітектур нейронних мереж, які можуть контролювати процес аналізу та виявлення захворювань. Пропонується розробити мережу, що складається з апаратного та програмного забезпечення, здатного передавати отримані дані з мікроскопа в хмарне сховище для подальшого використання згортковою нейронною мережею для класифікації зображень мазка крові людини для виявлення здорових або онкологічних клітин крові. Розроблено апаратно-програмний комплекс для збору та передачі значень з мікроскопа в хмарне сховище. Основним модулем прийому та передачі даних у хмару є одноплатний комп'ютер Raspberry Pi, який працює за технологією Wi-Fi. Таким чином, запропонована система здатна забезпечити ефективність діагностики раку крові не тільки лімфобластного лейкозу, але й інших видів.*

Keywords: *convolutional neural network, acute lymphoblastic leukemia, image processing, streaming, cloud storage, remote access, Wi-Fi technology, single-board computer.*

Ключові слова: *згорткова нейронна мережа, гострий лімфобластний лейкоз, обробка зображень, потокова передача, хмарне сховище, віддалений доступ, технологія Wi-Fi, одноплатний комп'ютер.*

I. INTRODUCTION

Today, the disease of acute lymphoblastic leukemia remains a serious threat to people's health. As of 2020, leukemia is the leading cause of cancer morbidity and mortality worldwide, according to estimates published in the Journal of Hematology & Oncology. The number of deaths from acute lymphoblastic leukemia reaches 311,954 [1]. Currently, there are several options for diagnosing acute lymphoblastic leukemia, namely with the use of a general blood test, coagulation studies, peripheral blood smears and computer tomography. However, the biggest problem lies in the speed of diagnosis and performing manual research work. That is why the need for remote data transmission and their fast processing for diagnosing the disease has become very important.

The proposed solution consists in the development of a network for streaming microscopic images of peripheral blood smears and transferring them to the cloud for data processing in order to analyze and diagnose the disease of acute lymphoblastic leukemia based on convolutional neural networks. Such a solution will make it possible to create devices that transmit information from a digital microscope based on cheap and easy-to-use components.

II. LITERATURE ANALYSIS

Diagnosis of acute lymphoblastic leukemia is a direction that requires implementation and implementation of automated solutions, tools and methods. This is a very high step in medical engineering to create conditions for easy detection of disease in early stages and even prediction of disease risks based on data. For decades, scientists have focused on the automatic detection and classification of acute lymphoblastic leukemia and its subtypes, in order to receive a highly accurate diagnosis of the patient.

2.1. Machine learning technologies for classification of acute lymphoblastic leukemia

Today, five approaches of machine learning algorithms are actively used for the classification of leukemia. Using a Binary Classification Algorithm or SVM used to classify step sample images into lymphoid stem cells and myeloid stem cells. In 2014, researchers using SVM algorithms achieved 92% accuracy results. In general, support vector algorithms are defined by a classifier learning algorithm that works on the principle of recording the characteristics of shapes and textures for each kernel. One of the following technologies is the use of K-Nearest Neighbor classification algorithms of leukemic cells from normal blood cells. The k-NN algorithm classifies new objects based on similarity scores, assuming that similar things exist in close proximity. However, the application of k-NN to classify blasts in leukemic cells and classify cells into acute myeloid leukemia and acute lymphocytic leukemia achieves an accuracy of 80 %. Including the practice of using the Naïve Bayes classifier. Bayes' theorem is a simple probabilistic classifier with independent naive assumptions, meaning that the value of features does not depend on the presence or absence of any other features, and each of these features independently affects the probability. Since only a small dataset is required for training, it can estimate various parameters needed for classification [2]. Including, is a fairly common practice of applying deep learning. A convolutional neural network is a widely used deep learning algorithm in the field of biological image data processing. Such a technology involves manually extracting features, learning features directly from the image, and then convolving it with the input data for classification and obtaining relevant results. In general, the use of deep learning algorithms, namely convolutional neural networks, currently achieve an accuracy of 97,78 %.

2.2. Microscope data streaming technologies

In today's world, there are options for obtaining data from a microscope and analyzing them instantly. One such robotic fluorescence microscopy technology, for the process of identification and quantification of immunolabeled cells and analysis, uses the Ikoniscope imaging system. Images are captured using the device's high-resolution, high-sensitivity charge-coupled monochrome camera. Cell identification occurs in real-time using image analysis to detect and quantify antibodies and FISH signals. Preparations are first scanned at low magnification (·10) to identify cells carrying both immunolabeled markers. Selected target cells are then re-viewed at high magnification (·100) to verify and count FISH signals. Results are displayed using the IkoniLAN viewer, which allows evaluation of low-magnification images of all scanned fields as well as high-magnification images of target cells in all fluorescence channels [3]. It is important to note that stored information, unprocessed and processed images, processing results are available through a separate development server both in local computer networks and on the Internet. This technology takes about one hour to transmit images from the microscope for analysis and processing to detect cancer. However, a significant disadvantage of such a system is the correspondingly high cost, even not for a new model.

Turning our attention to fluorescence microscopy technology, it is worth noting that not too long ago, flow cytometry was combined with fluorescence microscopy to create flow cytometry, where an image of each cell is captured as it flows past a light source and a charge-coupled device detector. Flow cytometry combines high throughput with spatial imaging information of multiple fluorescence channels, as well as a bright field similar to transmitted light imaging and a dark field equivalent to side scatter in conventional flow cytometry [4]. The high-content data rapidly collected by flow cytometry is well suited for classifying cell phenotypes using machine learning, especially deep learning, given the large number of training images required for the application of deep convolutional neural networks, which can be applied to classify the resulting microscopic images in real time.

III. OBJECT, SUBJECT, AND METHODS OF RESEARCH

The object of the study is the process of streaming data of microscopic images directly from the microscope and their processing for the detection of acute lymphoblastic leukemia.

The subject of research is a network of streaming data from a microscope using a webcam based on microcontroller modules. Tasks that were set for the research are:

– an automated process of streaming data in an unlimited amount in a local computer network;
– data transfer from the monitoring point to the cloud via the Internet;
– data transfer from the cloud for classification of microscopic images by a convolutional neural network;
– viewing results of data analysis of microscopic images of a blood smear via the Internet from a computer.

Research methods: algorithms of convolutional neural networks for classification of microscopic images obtained from cloud storage.

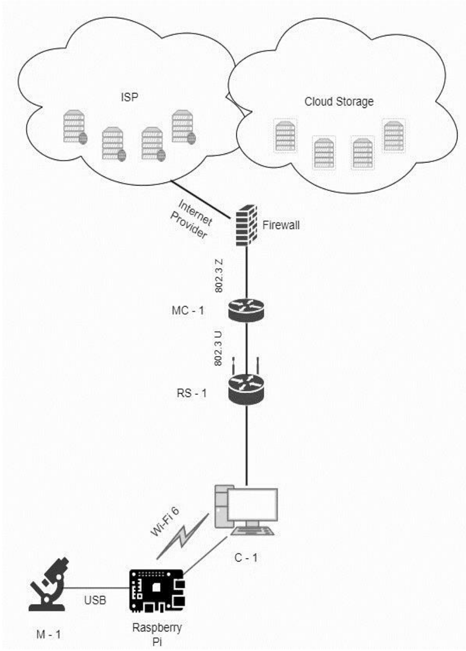

Fig. 1 – Netdiagram of data transfer from digital microscope to cloud storage

Practical significance: as a result of the conducted research, it will be possible to receive data through streaming images from a fluorescent microscope and process them by transmitting data from the cloud, using a convolutional neural network. Such results are important for the medical diagnosis of cancer, facilitating diagnostic processes and rapid detection of the disease in the early stages, which will ensure proper treatment and save the lives of patients.

IV. RESULTS

The result of the research is the analysis and selection of the hardware part, as well as the software part and relevant technologies for obtaining data from the microscope to the cloud and processing them for classification by a convolutional neural network.

4.1. Hardware components

During the research, the necessary hardware components were selected. Therefore, let us now consider the hardware part for collecting data from the microscope and transferring it to the cloud storage.

The Raspberry Pi single-board computer became the main controlling module responsible for receiving the image from the digital microscope and transferring it to the cloud storage. Let's take a closer look at a single-board computer (Fig. 2a). The key features of a single-board computer are a high-performance 64-bit quad-core processor, support for two displays with a resolution of up to 4k through a pair of micro-HDMI ports. Also, there are hardware video decoding in 4Kp60, from 1 to 4 · GB of RAM, dual-band wireless network at 2,4 and 5,0 GHz, Bluetooth 5.0, GbE, two USB 3.0 ports and PoE [9]. The power consumed by the Raspberry Pi kit is much less compared to general purpose computers. Using a USB camera will increase the power consumption as it will need a computer to operate, while the Raspberry Pi uses 5 V and 700–1800 mA which is much less than a general purpose computer, but has all the features it has on an ordinary computer [10].

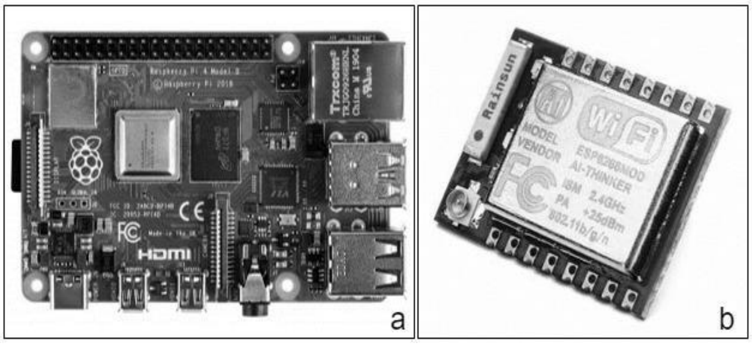

Fig. 2 – Hardware components of data transmission
a – Raspberry Pi 4 B, b – ESP8266 Wi-Fi module

Description of components:

1) Broadcom BCM2711 processor, Quad core Cortex-A72 64-bit SoC @ 1.5 GHz;
2) RAM 8GB LPDDR4-2400 SDRAM;
3) Connectivity: 2.4 GHz and 5.0 GHz IEEE 802.11ac wireless, Bluetooth 5.0, Gigabit Ethernet, 2 · USB 3.0 ports,

2 · USB 2.0 ports;

4) GPIO connector: Raspberry Pi standard 40 pin GPIO header;
5) 2 · micro-HDMI ports;
6) 2-lane MIPI DSI display port;
7) 2-lane MIPI CSI camera port;
8) 4-pole stereo audio and composite video port;
9) Multimedia support: H.265, H.264 and OpenGL ES 3.0 graphics;
10) Micro-SD card slot for loading operating system and data storage
11) 5 V DC via USB-C connector, 5 V DC via GPIO header, Power over Ethernet (PoE) enabled.

One of the powerful features of these mini-computers is the GPIO pins lined up along the top edge of the board. There are two 5 V pins and 3,3 V pins, as well as a set of ground pins (0 V) on the board. All remaining pins are general-purpose 3,3 V pins, and any of these pins can be assigned to the input or output pin on the software and can be used for various purposes [5].

The next step is the formation of a hemline between the digital microscope, a single-board computer and a hardware module that supports Wi-Fi data transmission to the wireless network. For such a task, we can use the inexpensive and affordable device ESP8266 (Fig. 2b). This is a Wi-Fi device, which means you can connect to it via Wi-Fi, but before that you need to configure it – the processor does not know the name of your local network and the password for connecting to it, as well as other possible settings. This, of course, is true for the case when we want the module to connect to our network. For the case when the module itself operates in access point mode, everything is a little more complicated. To simplify working with the module at the stage of programming and debugging your application, you can use the serial port (UART). The ESP8266 has a dedicated serial port for this – two ports labeled Rx and Tx. Tx is used to transmit data, and Rx is used to receive [6].

The ESP8266 module can operate both in Access Point mode and in Client workstation mode (station), and maybe in both modes simultaneously. Most often, the access point has an Internet connection and acts as a bridge between the device and the Internet. Several workstations on a local network also communicate with each other through an access point. The station can only be connected to one access point at a time. Each device on the network has its own unique MAC address – a 48-bit value. In addition, we can additionally connect a programming shield, which allows us to flash the board and communicate with it via USB ports. However, this is optional, that is, the main connection between the devices will be provided directly via Wi-Fi.

The hardware component responsible for video transmission is a digital microscope. The digital microscope (Fig. 3) can be connected to a Raspberry Pi single-board computer using a USB port and the resulting image can be transferred in real time to cloud storage via Wi-Fi.

Fig. 3 – Digital microscope PCE-MM800

The adjustable LED lighting of the digital microscope allows to illuminate the examined sample evenly from all sides. Including, it is such a device that allows you to take both photos and videos with the help of saving them. It is worth noting that a large digital microscope has a magnification of 200 to 1600 times, which allows viewing small objects with high detail, despite the visual simplicity of the device. The digital microscope has a CMOS matrix with a frame rate of 30 frames per second and a focal length of 10 mm. The use of a digital microscope will allow you to get two versions of images with a resolution of 640 · 480 or 1600 · 1200 pixels. Accordingly, a lower resolution can save cloud memory and speed up image processing by a convolutional neural network with a k-means algorithm [11] to separate the desired cells, where each class represents an image component (background, other non-target components) of the cells to be extracted. However, appropriate color processing should be provided to detect blast cells.

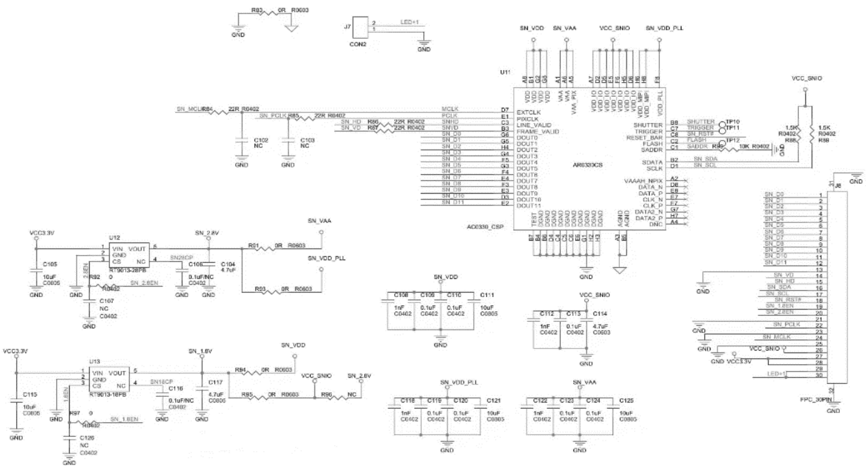

Fig. 4 – Circuit of digital microscope

4.2. Options for creating a network

In the course of the research, two options for creating a network for transmitting an image from a microscope to a computer were discovered. Namely, the study of the connection between a digital microscope and a single-board computer connected by a USB port and Wi-Fi protocol for data transfer and storage in cloud storage was performed (Fig. 5). The option of using and combining the hardware components of the microscope, HD camera and Wi-Fi module of the ESP was also considered. Let's look at each of them in a little more detail to find out the features.

4.2.1. Using a digital microscope with a Raspberry Pi

Communication between a digital microscope and a Raspberry Pi single-board computer occurs through a serial interface for connecting peripheral devices to computing equipment – USB.

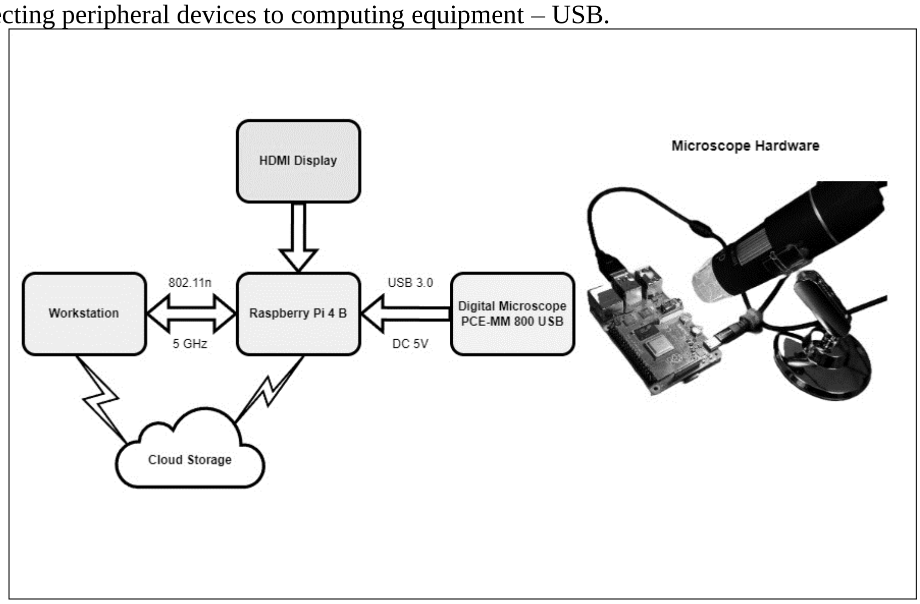

Fig. 5 – Block diagram of using digital microscope

Since the digital microscope includes a camera based on a CMOS matrix, it is enough to use a single-board computer that includes a Wi-Fi module for wireless communication to transfer data through the computer to cloud storage.

4.2.2. Using a microscope and Wi-Fi module

A light-sensitive eyepiece camera can be used to digitize the results of microscopic studies. This will allow you to broadcast the magnified image from the microscope to the computer monitor, take photos or videos. Compared to the matrices of other DCM cameras, the sensor of the digital eyepiece has the largest physical dimensions in pixels - 8 · 8 µm. Therefore, the sensitivity of the sensor will be greater. For some tasks, this coefficient more than compensates for the modest resolution of the matrix. Also, it is worth noting that the lens of such a camera has a multi-layer anti-reflective coating, which improves the light transmission of the glass and ensures the most correct color rendering. The maximum resolution of the image capture device is 640 · 480 pixels. The data transfer interface is USB 2.0. However, as we all know, the current version of the ESP8266 has either a micro-USB port or a Type-C port. Accordingly, to combine the Wi-Fi module and the camera, it will be necessary to use a special USB 2.0 adapter for the ESP module. The USB adapter is a small board, black in color with an eight-pin yellow connector, into which the ESP01 module is inserted, on the other side of the adapter there is a USB type A connector. Communication with the computer and the module is carried out by the CH340 microcircuit, next to it a quartz resonator at 12 MHz. Since the ESP8266 module works from 3,3 V the adapter provides a 3,3 V stabilizer (LM6206N3, maximum current 250 μA).

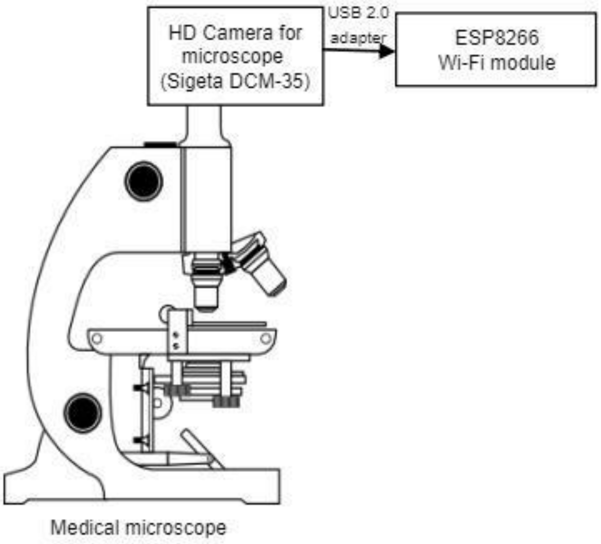

Fig. 6 – System Block Diagram

4.3. Software structure

Raspberry Pi can communicate serial data with other devices using some of the common serial communication protocols, such as UART, I2C, SPI, and USB. There are two UART ports/interfaces, two I2C ports, two SPI ports, and four USB ports on RPi 3B/4B. For our task, we will use the USB protocol for communication between a digital microscope and a single-board computer. In addition, a connection between a single-board computer and a personal computer should be provided for receiving data and transferring it via Wi-Fi to cloud storage. A more detailed diagram of the combination of the hardware part in a computer network can be seen on the network diagram (Fig. 1).

The image from the digital microscope through which the analysis of blood smears is carried out is sent in real time through Wi-Fi modules and the Internet provider to the virtual servers of the cloud storage, from where information will be transmitted to the decision-making center regarding the classification of the received digital images. The result of processed data will be available to a medical specialist using a separate program interface on a local computer. Data is stored in cloud storage to ensure constant access to it. Including, access to data can be controlled through the application for re-viewing or re-checking using a neural network.

4.3.1. Image processing

The general structure of the architecture of the neural network with the help of which training and processing of images from the microscope will take place is shown in the block diagram (Fig. 7). The architecture of the convolutional neural network is sequential, accordingly, each stage of the algorithm proceeds step by step. First, the software code goes through all the data to find the available and required directories on the cloud storage where the microscope images are stored. This is followed by the stage of training and testing data frames, determining the necessary parameters of the learning model, and determining the required number of images and labels for analysis and processing.

It is also important to generate data and extract sample images for further processing to enable diagnosis based on color parameters.

```
def show_images(gen):
    g_dict = gen.class_indices
    classes = list(g_dict.keys())
    images, labels = next(gen)
    length = len(labels)
    sample = min(length, 25)
    plt.figure(figsize= (20, 20))
    for i in range(sample):
        plt.subplot(5, 5, i + 1)
        image = images[i] / 255
        plt.imshow(image)
        index = np.argmax(labels[i])
        class_name = classes[index]
        plt.title(class_name, color= 'blue', fontsize= 12)
        plt.axis('off')
    plt.show()
```

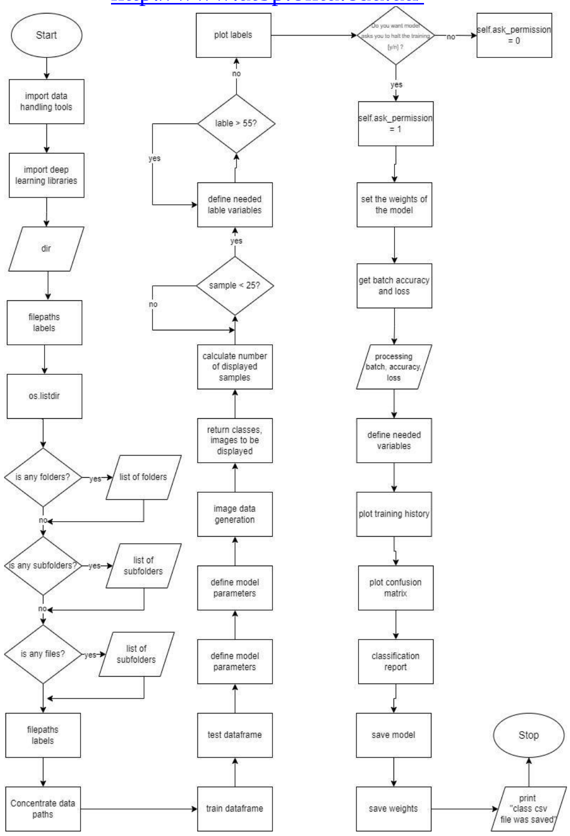

Fig. 7 – Flowchart of image processing algorithm

This program code defines a data dictionary, defines a list of classes) of the dictionary, class names, and defines the received lot size samples from the generator. Including, the program code performs the task of calculating the number of displayed samples, the length of the batch size and checks the minimum number of images in the sample.

When a neural network tries to learn too much detail in the training data along with noise from the training data, it results in poor performance on the unseen or test data set. Overfitting during training can be observed when the error of the training data decreases to a very small value, but the error of the new or test data increases to a large value [14]. One of the options for solving this problem was weight regularization. Weighted regularization reduces overfitting by penalizing or adding constraints to the loss function. Regularization terms are constraints that an optimization algorithm such as stochastic gradient descent must obey when minimizing a loss function. Several mathematical conditions have been developed for weight regulation that reduces overfitting by penalizing or adding constraints to the loss function. Such conditions must be observed by the neural network. By adding a weight penalty to the loss function, the overall loss of the neural network increases. The optimizer will now be forced to minimize the network weights as this contributes more to the overall loss.

Let's define the first condition (1), when penalty functions should be applied. From B – the number of neurons in the previous layer of the convolutional neural network, the activation function of which has not reached a certain value.

$$B = \frac{count(B^c)}{\sqrt[2]{3}}, \tag{1}$$

where B^c – coefficient of the number of neurons (2),

$$B^c = \{C(n-2) | f(x)_{ReLU} > \frac{\max(x)}{2}\}, \tag{2}$$

where C – number of neurons,

$n-2$ – the previous layer,

$f(x)_{ReLU}$ – the linear function of the Rectifier Linear Unit.

The Rectifier Linear Unit (ReLU) [13] is the most commonly used activation function in CNN. It is used to convert all the input values to positive numbers. The advantage of ReLU is that it requires very minimal computation load compared to others. The mathematical representation of ReLU (3).

$$f(x)_{ReLU} = max\ (0, x), \tag{3}$$

The second condition for applying the penalty function is the case when the neural network produces a conditional distribution for classes with given x values through functions. In order to penalize the original distributions, it is necessary to determine the difference in the degree of disorder in the layers of neurons and the probability during the training of the neural network. Such a difference will be determined by the formula (4).

$$L = -\sum \log p_i(y|x) - kH(p_i(y|x)), \tag{4}$$

where k – coefficient of control of the force of the penalty,

H – entropy,

p_i – the probability during the training.

The i^2 regularization forces the network's weights to decay towards zero (but not equal to zero) by adding a penalty term equal to the "squared magnitude" of the coefficient to the loss function. It regularizes the weights by heavily penalizing the larger weight vectors. This is done by adding to the objective function, where λ is a hyper-parameter, which decides the strength of penalization and k denotes the matrix norm of network weights. To determine such a function, we determine the set of coefficients P of the penalty function (5).

$$P = \left\{\frac{1}{V}\middle| V \in N^p\right\}, N^P = \left[2, 4, 6, \dots, 2 \times i + 1 \middle| i \in [0; 4]\right], \quad (5)$$

Consider a network with only a single hidden layer and with parameters w [12]. If there are N neurons in the output layer and the prediction output and the actual output are denoted by y_n and p_n, where $n \in [0, N]$. Then the objective function (6).

$$CostFunction = loss + p\lambda\|\omega\|^2, \quad (6)$$

where $p \in P$. In the case of euclidean objective function (7).

$$CostFunction = \sum_{m=1}^{M}\sum_{n=1}^{N}(p_n - y_n)^2 + p\,\lambda\|\omega\|^2, \quad (7)$$

where M is a number of training examples. Now the weight incrementation rule with the i^2 regularization will be as (8).

$$WeightIncrement = argmin \sum_{m=1}^{M}\sum_{n=1}^{N}(p_n - y_n)^2 + \lambda\|\omega\| \quad (8)$$

Before being used for further categorization, the resulting visual data must first go through a process called feature extraction, in which it is transformed into a specific collection of features and labeled. Each object in an image can be analyzed for various characteristics, including shape characteristics (area, perimeter, and strength), texture characteristics (uniformity, energy, second of angle, and others), statistical characteristics (mean, skewness, and variance), geometric characteristics (perimeter, area, compactness and symmetry) and color characteristics [8]. Because blast cells carry a wealth of information, including information about their cytoplasm and nucleus, the stage of feature selection is critical in determining the type of acute leukemia. For convenience when identifying features, an intelligent edge detection algorithm is applied to each image. To smooth the image and get rid of noise, a Gaussian filter is used (Fig. 8).

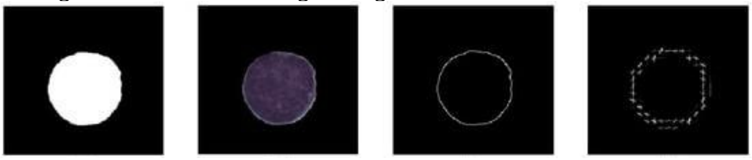

Fig. 8 – Examples of images after processing

4.3. Results Analysis

Files from the digital microscope are sent to the cloud storage in JPG format. The overall data processing takes place sequentially according to a convolutional neural network. The image processing module allows automatic extraction of relevant features of input images, which in acute lymphoblastic leukemia is usually the entire cell region with edges to improve model performance (Fig. 9). Feature maps focus more on cell area and edges [7].

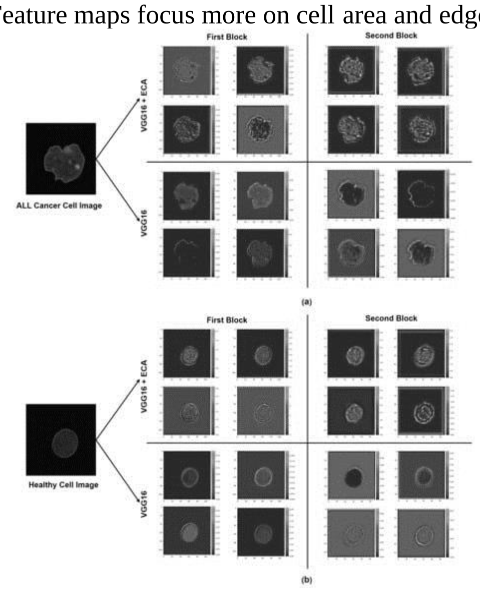

Fig. 9 – Feature maps created by the cancer and healthy cell classification module

Taking into account the complexity and duration of neural network training, an active learning process continues today. Relevant results of neural network training accuracy for image processing obtained from datasets have been generated. The results are shown in Table 1.

Table 1. The result of image classification by the model of CNN

Classes	AUC, %	Accuracy, %	Sensitivity, %	Precision, %	Specificity, %
ALL	98,2	97,1	97,2	97,3	94,2
Normal	95,3	94,2	94,3	93,8	97,1
Average ratio	96,75	96,2	95,75	95,55	95,65

As we can see in the table of obtained training results for the dataset, the neural network training accuracy reaches

96,2 % on average. Accuracy and sensitivity results for processed images can be improved by increasing the amount of data, including not only data from open sources on the Internet. However, at the moment, the training of the neural network is performed properly, including the processing of images in JPG format.

V. CONCLUSIONS

The use of streaming technology combined with cloud storage provides a dynamic solution that holds promise for improving the efficiency and accuracy of acute lymphoblastic leukemia disease detection. Streaming microscopic image data to cloud storage enables real-time analysis, reducing the overall diagnostic time of specialists. Such a timely diagnosis significantly affects treatment planning and its effectiveness by 15,5 %. In particular, cloud data storage of up to 9 GB allows you to store and process huge amounts of digital microscope image data. This scalability ensures that the system can efficiently process a large volume of medical images. In addition, the flexibility of cloud infrastructure makes it easier to adapt to the changing demands of healthcare. However, it should be noted that when using one hardware complex for diagnostics, the continuous transmission of high-resolution microscopic images can lead to network overload. This can cause delays and affect real-time system performance. Therefore, the further reduction of network congestion by 6,78 % is critical to ensure smooth and efficient streaming of microscopic image data in the context of acute lymphoblastic leukemia and other disease types. The developed hardware and software system for collecting and transmitting microscopic images using Wi-Fi technology allows both accumulating and processing sufficient amounts of data on remote network resources in real time. The use of information technologies and automation tools in this study will allow for quick identification of 257,85 seconds possible disease of the patient according to the medical image. In the future, the data transmission network can be improved to prevent cloud server overload cases through data compression, techniques for distributing data content to multiple servers, and improving image classification results using a convolutional neural network.

VI. REFERENCES

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