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An Enhanced Analysis of Blood Cancer Prediction Using ANN Sensor-Based Model †

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Abstract: Blood cancer diagnosis is a critical medical procedure, yet difficult and expensive for clinical personnel to perform accurately. Artificial neural networks have been shown to be effective in diagnosing a range of diseases, due to their powerful ability to identify and classify patterns in data. Here, we present a study that employed one such ANN to diagnose blood cancer from data gathered from network sensors. First, a sensor network was placed in an animal model to capture various physiological data, including cardiac and respiratory rates, body temperature, and blood pressure. This data was then sent to an ANN which used a classification system based on the type of cancer for diagnostic analysis. Our results showed that the ANN was able to accurately diagnose a blood cancer with an accuracy of 92.1% and that its accuracy improved with the addition of more data. Our study demonstrates that ANNs can be successfully used to accurately diagnose blood cancer using data from network sensors, which could reduce costs and provide faster results in clinical settings.

Keywords: blood cancer; medical; clinical test; ANN; sensor

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1. Introduction

Blood cancer is a term used to collectively refer to various types of cancers that affect the blood, bone marrow, and lymph nodes. These cancers include various forms of leukemia, lymphoma, and myeloma [1]. It can be difficult to recognize the signs and symptoms of blood cancer because they can vary greatly between people. However, common signs and symptoms include fatigue, fever, night sweats, unexplained weight loss, swollen lymph nodes, and repeat infections. Therefore, it is important to be aware of these signs and seek medical attention if any of them persist. Effective diagnosis of blood cancer is vital to detecting the disease in its early stages [2]. The diagnosis of blood cancer is an extremely important step in providing successful treatment and outcomes. Early detection allows doctors to act and provide the best possible care. If you are experiencing signs and symptoms of blood cancer, it is important to seek medical advice and get tested [3]. Flow cytometry is a useful tool for looking at individual cells to identify abnormal characteristics. This particular technique involves taking a sample of blood and filtering it through nanosized particles that are biocompatible and looking for biological indicators of cancer [4]. Some newer technologies have been developed that utilize a combination of many traditional methods as well as genetic, biomarkers, immunological, and proteomic studies to identify changes in biomarkers that are suggestive of the presence of cancer. As technology continues to advance, newer and improved methods of diagnosis are sure to follow [5]. The main contribution of our research includes the following:

Early Detection: Early diagnosis of blood cancer increases the chance of successful treatment, reduces the severity of symptoms, and lowers the risk of mortality.

Accurate Screening: Regular screenings provide a detailed understanding of the patient's condition and help doctors identify and diagnose cancer at an early stage.

Effective Treatment: Diagnosis of blood cancer helps healthcare professionals provide the most effective treatment for individual patients [6–9].

An Artificial Neural Network (ANN) sensor-based model can be used to enhance the analysis of blood cancer prediction. This model can utilize state-of-the-art deep learning technologies to detect subtle variations in the data that may be indicative of a higher risk of developing cancer. Sensor-based models can take input from a variety of sources, including images and sound, which can provide additional information that traditional models may not be able to detect. ANNs can be used to analyze images of cells obtained from blood samples to detect patterns that may signify the presence of cancerous cells. This information can then be combined with other data such as patient demographics and medical history to create a more detailed picture of a patient's risk for developing cancer.

2. Materials and Methods

Blood cancer is a serious illness that affects hundreds of people every year. Unfortunately, the diagnosis process for blood cancer can be complicated and lengthy. To effectively diagnose and treat the condition, medical professionals need to understand the different aspects of blood cancer and how it affects the body [10]. Additionally, the doctor may order imaging tests such as X-rays, CT scans, and Magnetic Resonance Imaging (MRI) to get a better view of the patient's body [11]. If the biopsy reveals high levels of abnormal cells, a diagnosis of cancer can be made. It is important to note that if the biopsy does not turn up any cancer cells, the patient may still be at risk for developing the condition in the future [12]. There are three main types of blood cancer—leukemia, lymphoma, and myeloma. For this purpose, doctors may need to use a variety of tests including flow cytometry and molecular analysis. Doctors need to diagnose the right type of cancer as treating the wrong one can cause unnecessary issues [13–15]. A blood cancer diagnosis is a complicated issue and one that requires a multifaceted approach. First, medical practitioners need to be informed and knowledgeable about the variety of both hematological (blood-related) and non-hematological cancers. Once an individual is suspected or determined to have blood cancer, there are a variety of tests that can be conducted to determine the type and stage of cancer [16,17]. Treatment options are based on the type and stage of the cancer. Common treatments include chemotherapy, radiation, and/or surgery. Each of these treatments comes with its own set of challenges [18]. This includes regular check-ups, blood tests, and careful tracking of any symptoms that may develop. These steps can help to ensure that any side effects or complications from treatment are monitored and managed [19]. The novelty of blood cancer diagnosis by artificial neural network analysis of data from network sensors is that it uses deep learning techniques to analyze data from network sensors, which facilitates early detection and accurate diagnosis of blood cancer [20].

Proposed Model

Blood cancer diagnosis by artificial neural network analysis of data from network sensors is an application of machine learning and artificial intelligence techniques. It is an evolving field of research and will help in the diagnosis of various types of cancer such as leukemia, lymphoma, and multiple myeloma.

$$C_d = \{c_1, c_2, c_3 \ldots\ldots, c_n\} \tag{1}$$

$$D_o = \{d_1, d_2, d_3 \ldots\ldots, d_m\} \tag{2}$$

$$G = C_d + D_c \tag{3}$$

Once the symptom is identified, the system can classify the type of cancer. The neural network analysis also helps in monitoring treatments and disease progress. Blood cancer is a serious illness with many complex and variable characteristics that require a precise, comprehensive diagnosis to ensure proper medical treatment.

$$D = \frac{1}{2} * \pi C^3 * v \quad (4)$$

An Artificial Neural Network is a computer system modeled after the human brain's neural networks.

$$C_d = \sqrt{\frac{2C * \left(\frac{1}{2} * \pi C^3 * v\right)}{C}} = \sqrt{\frac{2D * \pi * C^2 * v}{3}} \quad (5)$$

Artificial Neural Networks can determine the presence of blood cancer by analyzing this data to identify patterns, correlations, and anomalies that are associated with typical blood cancer characteristics, such as size, shape, and texture.

$$G = \{c_1, c_2, c_3 \ldots\ldots, c_n\} + \{d_1, d_2, d_3 \ldots\ldots, d_m\} \quad (6)$$

$$G_d = \sum_{d=1}^{\infty} c_{x(d-1)} + d_{y(d-1)} \quad (7)$$

The use of network sensors and Artificial Neural Networks for blood cancer diagnosis is an exciting development in the field of medical technology. By using network sensor data from a patient's vital signs, such as heart rate, body temperature, breathing rate, and other biological indicators, the machine learning system can analyze the data and determine if there are signs of cancer.

$$C_d = 2C * \sqrt{\frac{2 * \pi D v}{3}} = D * \sqrt{\frac{2 * \pi D v}{3}} \quad (8)$$

The machine learning system will then produce a prediction, which can alert medical professionals for further evaluation and treatment. In this method, an artificial neural network is used to process patient data. The effectiveness of Artificial Neural Networks (ANNs) in diagnosing diseases, particularly blood cancer, can vary, depending on the type of data being analyzed and the type of ANN used. Since ANNs are designed to learn from past data, they can become proficient at recognizing patterns and classifying data. Studies have shown that in certain instances, ANNs can outperform human experts in diagnosing certain diseases, namely in the realm of medical imaging. This can be done by inputting large amounts of medical images into the ANN to assist in diagnosing a certain disease or condition. Such is the case with precision diagnostics of lung cancer through CT scans which have even been proven to outperform human experts in certain cases.

1. Designing the Sensor System: The first step of this process is to design an appropriate sensor system that will capture the data needed for the ANN. This sensor system should be able to optimize data collection from the animal model efficiently and effectively. The sensor system should also be designed to minimize any interference or discomfort to the animal that may result from its use.

2. Placing the Sensor System: Once the sensor system has been designed, it can be placed on the animal model. Depending on the type of data that is being collected, this step may involve threading sensors into the model's fur or attaching an external sensor system to its body.

3. Collecting Data: After the sensor system has been placed on the animal model, the data collection process can begin. This process involves collecting information such as body temperature, heart rate, and other biological factors from the sensor system. This data is then collected over a period of time to determine the effects of the animal's environment or behavior on its physiology.

4. Analyzing Data: After the data has been collected, it needs to be analyzed to determine its usefulness for ANN. This may involve running various tests on the data to determine patterns in sensor readings or identifying areas of interest for further research.

5. Constructing the ANN: Once the data has been analyzed and the areas of interest have been identified, the ANN can be constructed. This involves connecting the sensors to the ANN and programming the ANN to recognize patterns within the data.

6. Training the ANN: At this stage, the ANN must be trained on the data that has been collected to accurately recognize patterns in the data. This can involve adjusting the weights assigned to each sensor, as well as running various tests to ensure the accuracy of the ANN.

7. Evaluating the ANN: Finally, the ANN must be evaluated to determine its effectiveness in recognizing patterns within the data. This can involve running actual tests on the ANN using the data collected from the animal model, to determine its accuracy and its ability to recognize patterns.

The functional block diagram is shown in the following Figure 1.

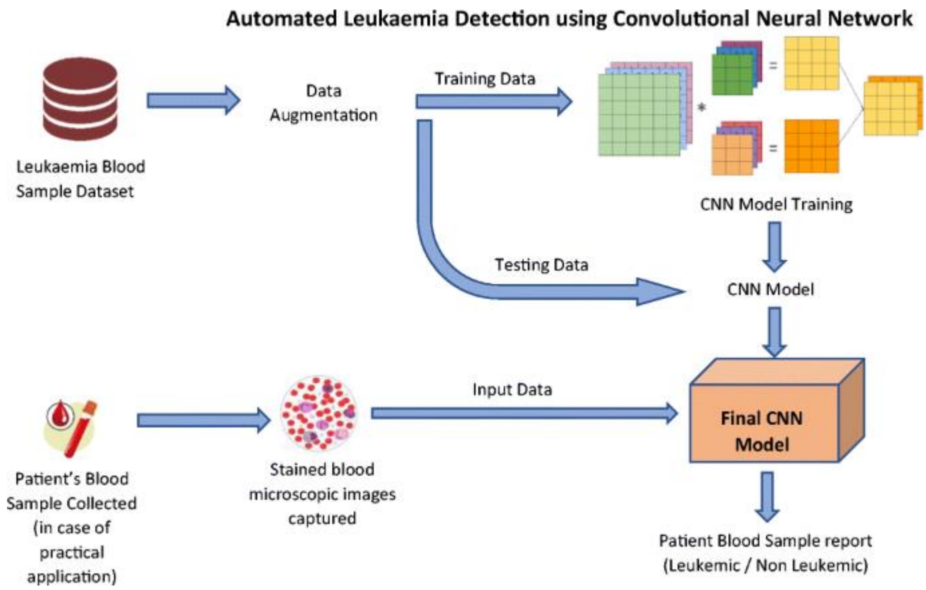

Figure 1. Functional Block diagram.

It is used to analyze large sets of data and extract meaningful patterns and relationships. In the case of blood cancer diagnosis, the ANN-based artificial intelligence system is used to predict the likelihood of a person developing a particular type of cancer-based on their current medical profile and the changes in their vital signs over time.

$$d(c) = d_1(c) * d_2(c) \tag{9}$$

$$c(d) = c_1(d) * c_2(d) \tag{10}$$

$$G = \left\{ \frac{d(c) + c(d)}{c(d,c)} \right\} \tag{11}$$

Blood cancer diagnosis using the Artificial Neural Network (ANN) analysis of data from network sensors is a promising technology that has the potential to revolutionize how blood cancers are diagnosed.

$$G = \left\{ \frac{(d_1(c) * d_2(c)) + (c_1(d) * c_2(d))}{d(d,c) * c(d,c)} \right\} \tag{12}$$

$$d(c) = \{c_1 * d_1(c) + C_2 * d_2(c) + \ldots\ldots + D_c * c_d(d)\} \tag{13}$$

The blood cancer diagnosis using ANN is so effective is because the data that is collected and fed to the ANN system is very specific and relevant to the patient's medical profile. The operational flow diagram is shown in the following Figure 2.

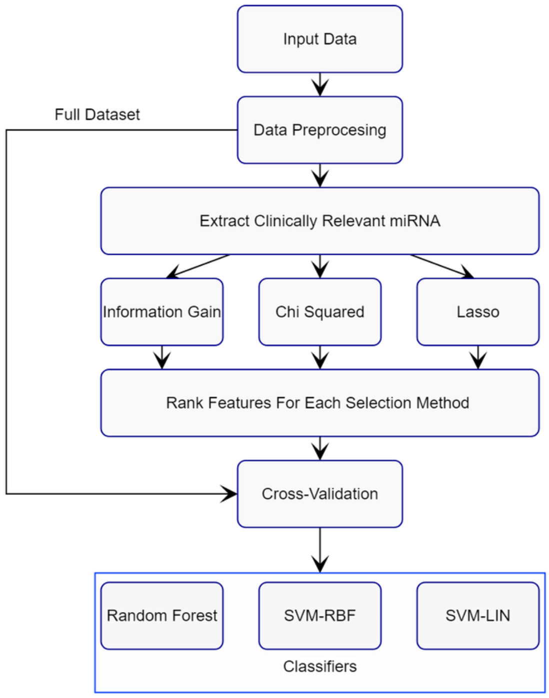

Figure 2. Operational Flow diagram.

This means that the system can accurately identify patterns and anomalies in the data that could potentially indicate the presence of a particular type of cancer. Another advantage of this technology is that it does not require any invasive procedures to collect the data. The sensor network can capture a wide range of physiological data, all of which can be used to monitor and track the general health of a patient. Cardiac and respiratory rates are monitored to assess the function of the heart and lungs and monitor for any abnormalities. Body temperature can help identify any changes in temperature due to a patient's illness or infection, as well as detect any potential fever. Lastly, blood pressure readings are taken to monitor the patient for any changes in blood pressure and ensure that the patient is receiving the appropriate amount of blood flow to the organs. All this data can be used to effectively assess and monitor a patient's health and provide a better understanding of their overall health status. An ANN can be used to carry out a classification process to diagnose blood cancer based on patient data. The process begins by first identifying a set of patient data that would be relevant to the diagnosis. This data could include a patient's medical history, various lab tests, imaging results, and other similar data. After the relevant data is identified, it can be fed into the ANN to train the model on the different types of blood cancer. The ANN can then be used to classify the patient data and make predictions on the possible type of blood cancer the patient may have. This classification process is done through a supervised learning process, where the ANN is trained on a training data set that is labeled with the diagnosis. Once the ANN is trained, it can be tested on new data with unlabeled diagnoses and used to make predictions on the type of blood cancer that is present. The accuracy of the ANN's predictions can then be evaluated to determine its efficacy.

3. Results and Discussion

The proposed model has been compared with the existing Bayesian Convolutional Neural Network (BCNN), Bayesian-based Optimized CNN (BOCNN), Cancer Prognosis Prediction (CPP), and Acute Lymphoblastic Leukemia Detection (ALLD).

The Critical Success Index (CSI) is a statistical measure used to measure the success of a given outcome in the field of artificial intelligence and machine learning. It is used to measure the predictive accuracy of an Artificial Neural Network (ANN) when diagnosing a given disease.

Figure 3 shows the comparison of the critical success index. In a computation cycle, the proposed model reached an 87.33% critical success index. The existing BCNN achieved 40.05%, BOCNN reached 39.92%, CPP reached 70.17% and ALLD obtained a 71.26% critical success index.

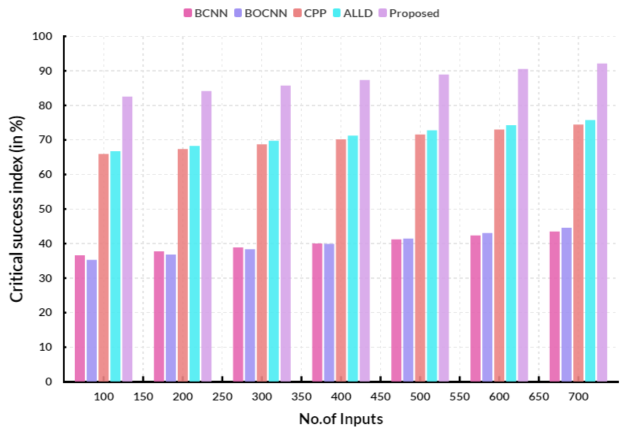

Figure 3. Critical success index.

The prevalence threshold for blood cancer diagnosis by Artificial Neural Network analysis of data from network sensors is a method used to detect the presence of a certain type of cancer. The analysis uses the network's sensor data to create a classification model, which is then used to detect the presence of the target disease.

Figure 4 shows the comparison of the prevalence threshold. In a computation cycle, the proposed model reached an 83.99% prevalence threshold. The existing BCNN achieved 39.63%, BOCNN reached 34.51%, CPP reached 71.32%, and ALLD obtained a 68.49% prevalence threshold.

Figure 4. Prevalence threshold.

The phi coefficient is a measure of the correlation between two different sets of categorical data. It is used to assess the strength of the relationship between two variables, and it is often used in medical research to evaluate how successful a diagnostic tool is.

Figure 5 shows the comparison of the phi-co-efficient. In a computation cycle, the proposed model reached 84.60% phi-co-efficient. The existing BCNN achieved 40.17%, BOCNN reached 36.50%, CPP reached 69.12%, and ALLD obtained 68.16% phi-co-efficient.

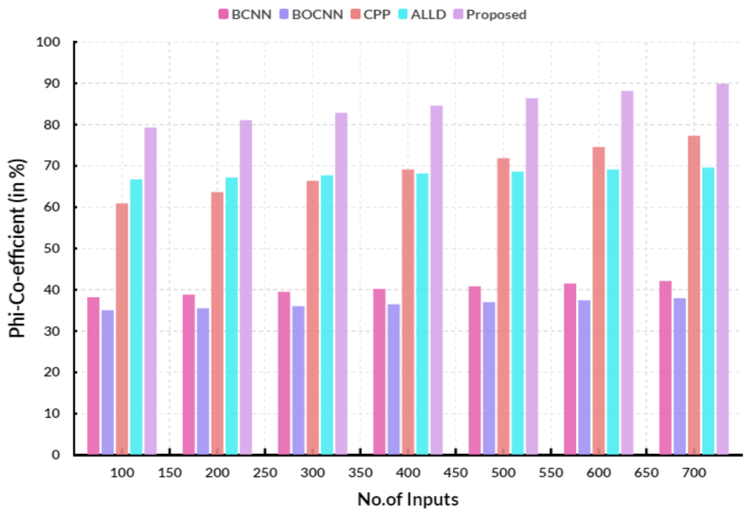

Figure 5. Phi-Co-efficient.

- The potential of misdiagnosis and false-negative results can lead to severe, expensive, and sometimes life-threatening consequences.
- Screening tests, such as a complete blood count (CBC) and immunophenotyping, may lack sensitivity and specificity.
- Traditional laboratory tests are costly and time–consuming and may not be suitable for mass screening.
- Current biomarker panels are often limited to detecting only one or a few blood cancer types, making them inadequate for effective diagnosis.

Blood cancer, specifically leukemia, is an aggressive form of cancer that tends to spread rapidly because cancerous cells grow quickly and spread to other organs. When left undiagnosed, the cancer will get worse, and the cancer cells can quickly and easily spread to other areas of the body. This can cause the cancer to become harder to treat. Blood cancer can also be aggressive if it manifests into an acute form since acute forms of the disease tend to progress much faster than the more common chronic form. If left undiagnosed and untreated, blood cancer can cause severe physical and emotional problems, and in some cases even death.

1. ANN-based diagnostics can provide more accurate and tailored diagnoses leading to better outcomes for patients.

2. ANNs can reduce medical errors by making more accurate diagnoses more quickly and taking into consideration a much wider range of factors, including lab tests or scans.

3. AI-based diagnostic systems are cost-effective as they allow for faster and more efficient diagnosis with significantly fewer errors compared to traditional diagnostic methods.

4. AI-based solutions can eliminate the need for complex tests and procedures, thereby reducing costs.

5. AI-based systems are also more resilient to environmental factors such as changes in the patient's medical history or external events, allowing for more accurate diagnoses.

6. The use of AI-based diagnostic systems can empower clinicians to focus more on treating patients rather than diagnosing them.

7. The use of AI-based diagnostic systems can reduce the physical burden on health workers, potentially leading to improved job satisfaction and satisfaction among patients.

Accurate diagnosis is essential to ensure that the patient receives the most effective treatment possible. When a patient is accurately diagnosed, the doctor can develop an effective treatment plan, which can include medications, therapies, and other interventions, tailored to the patient's condition. Accurate diagnosis also helps prevent unnecessary treatments and false diagnoses. By providing the most accurate diagnosis, the medical practitioner can ensure better outcomes for the patient, as well as improved cost-effectiveness and efficiency of the healthcare system.

4. Conclusions

Blood cancer diagnosis is a difficult and complex process that can involve evaluating a patient's medical history, physical examinations, blood tests, imaging tests, and biopsies. Artificial Neural Network analysis of data from network sensors is a relatively new approach that has been used to diagnose blood cancer. This technique uses a combination of Artificial Neural Networks (ANN) and data collected from network sensors to identify the presence of cancerous cells. ANNs are composed of interconnected computational nodes that are capable of learning how to recognize patterns from data. It may be less invasive and more accurate than traditional methods and can be used to diagnose even the rarest forms of blood cancer. Despite the advantages of this approach, there are still some challenges. One of the main challenges trusts the accuracy of the ANNs since they are still in the early stages of development. The ANN's applicability to other medical conditions in blood cancer detection or analyzing whether other cancer types can be detected by ANNs or using Bayesian methods for cancer detection. Additionally, more research can be done to increase the accuracy and speed of the detection process, so that it can be used for real-time clinical applications. Finally, further research should be done to capitalize on the cost and scalability of ANNs for cancer detection, especially in developing countries, so that more people can access life-saving treatments.

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References

1. Sinha, K.; Uddin, Z.; Kawsar, H.I.; Islam, S.; Deen, M.J.; Howlader, M.M.R. Analyzing chronic disease biomarkers using electrochemical sensors and artificial neural networks. *TrAC Trends Anal. Chem.* **2022**, *158*, 116861. [CrossRef]
2. Billah, M.E.; Javed, F. Bayesian convolutional neural network-based models for diagnosis of blood cancer. *Appl. Artif. Intell.* **2022**, *36*, 2011688. [CrossRef]
3. Karar, M.E.; Alotaibi, B.; Alotaibi, M. Intelligent medical IoT-enabled automated microscopic image diagnosis of acute blood cancers. *Sensors* **2022**, *22*, 2348. [CrossRef] [PubMed]
4. Atteia, G.; Alhussan, A.A.; Samee, N.A. Bo-allcnn: Bayesian-based optimized cnn for acute lymphoblastic leukemia detection in microscopic blood smear images. *Sensors* **2022**, *22*, 5520. [CrossRef] [PubMed]
5. Pathak, R.K.; Mishra, S.; Sharan, P. Design of optical sensor for cancer prognosis prediction using artificial intelligence. *J. Opt.* **2023**. [CrossRef]
6. Tuba, E.; Strumberger, I.; Tuba, I.; Bacanin, N.; Tuba, M. Acute lymphoblastic leukemia detection by tuned convolutional neural network. In Proceedings of the 2022 32nd International Conference Radioelektronika (RADIOELEKTRONIKA), Kosice, Slovakia, 21–22 April 2022.
7. Bratchenko, I.A.; Bratchenko, L.A. Comment on "Quantification of glycated hemoglobin and glucose in vivo using Raman spectroscopy and artificial neural networks". *Lasers Med. Sci.* **2022**, *37*, 3753–3754. [CrossRef] [PubMed]

8. Sandhya, P.; Gandhewar, N. A Novel Big Data Handling Approach Using Fuzzy Rule Based Artificial Neural Network. *Scand. J. Inf. Syst.* **2023**, *35*, 406–412.
9. Huyut, M.T.; Velichko, A. Diagnosis and Prognosis of COVID-19 disease using routine blood values and LogNNet neural network. *Sensors* **2022**, *22*, 4820. [CrossRef] [PubMed]
10. Sbrollini, A.; Tomassini, S.; Sharaan, R.; Morettini, M.; Dragoni, A.F.; Burattini, L. Leukocyte classification for acute lymphoblastic leukemia timely diag-nosis by interpretable artificial neural network. *J. Auton. Intell.* **2023**, *6*, 1–9.
11. Mohammedqasim, H.; Ata, O. Real-time data of COVID-19 detection with IoT sensor tracking using artificial neural network. *Comput. Electr. Eng.* **2022**, *100*, 107971. [CrossRef] [PubMed]
12. Velichko, A.; Huyut, M.T.; Belyaev, M.; Izotov, Y.; Korzun, D. Machine learning sensors for diagnosis of COVID-19 disease using routine blood values for internet of things application. *Sensors* **2022**, *22*, 7886. [CrossRef] [PubMed]
13. Arora, T.; Kaur, M.; Nand, P. Deep Learning Methods for Chronic Myeloid Leukaemia Diagnosis. In *Trends and Advancements of Image Processing and Its Applications*; Johri, P., Diván, M.J., Khanam, R., Marciszack, M., Will, A., Eds.; Springer: Berlin/Heidelberg, Germany, 2022; pp. 145–163.
14. Zeng, Q.; Chen, C.; Chen, C.; Song, H.; Li, M.; Yan, J.; Lv, X. Serum Raman spectroscopy combined with convolutional neural network for rapid diagnosis of HER2-positive and triple-negative breast cancer. *Spectrochim. Acta Part A Mol. Biomol. Spectrosc.* **2023**, *286*, 122000. [CrossRef] [PubMed]
15. Goel, A.; Goel, A.K.; Kumar, A. The role of artificial neural network and machine learning in utilizing spatial information. *Spat. Inf. Res.* **2023**, *31*, 275–285. [CrossRef]
16. Das, P.K.; Diya, V.A.; Meher, S.; Panda, R.; Abraham, A. A systematic review on recent advancements in deep and machine learning based detection and classification of acute lymphoblastic leukemia. *IEEE Access* **2022**, *10*, 81741–81763. [CrossRef]
17. Patil, V.N.; Ingle, D.R. A Novel Approach for ABO Blood Group Prediction using Fingerprint through Optimized Convolutional Neural Network. *Int. J. Intell. Syst. Appl. Eng.* **2022**, *10*, 60–68. [CrossRef]
18. Popescu, D.; El-Khatib, M.; El-Khatib, H.; Ichim, L. New trends in melanoma detection using neural networks: A systematic review. *Sensors* **2022**, *22*, 496. [CrossRef]
19. Pantic, I.; Paunovic, J.; Cumic, J.; Valjarevic, S.; Petroianu, G.A.; Corridon, P.R. Artificial neural networks in contemporary toxicology research. *Chem.-Biol. Interact.* **2022**, *369*, 110269. [CrossRef] [PubMed]
20. Sakthiraj, F.S.K. Autonomous leukemia detection scheme based on hybrid convolutional neural network model using learning algorithm. *Wirel. Pers. Commun.* **2022**, *126*, 2191–2206. [CrossRef]