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RESEARCH ARTICLE

Pattern Recognition of Acute Lymphoblastic Leukemia (ALL) Using Computational Deep Learning

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ABSTRACT Leukemia is a cancer of blood-producing cells, including the bone marrow. Abnormal white blood cells travel through blood vessels and multiply rapidly. Healthy cells in the body become a minority, and the imbalance increases the chances of infection in the body. Leukemia or blood cancer is the most common cancer in children ages 2 - 14. Most leukemia in children is treated. Acute lymphocytic leukemia (ALL) is a type of cancer in the blood and bone marrow. It progresses rapidly when immature white blood cells are formed instead of mature ones. Treatments for acute lymphocytic leukemia include drugs and blood transfusions directly into veins, chemotherapy, and all transplantation, which involve transferring organs or tissues within the body or from one person to another. In this paper, Pattern Recognition of Acute Lymphoblastic Leukemia has been proposed using Computational Deep Learning. Pattern recognition technology uses mathematical algorithms to identify patterns in large datasets of data. Analyzing the data, the algorithms can identify patterns indicative of certain states or conditions. In the case of ALL, the algorithm would look for patterns in white blood cell count data that indicate the presence of ALL. These patterns may include changes in the number of white blood cells over time, changes in the composition of the white blood cells, or changes in the levels of certain proteins or gene expressions associated with ALL. The proposed ALLDM model achieved 81.53% (DDS) and 87.92% (SDS) of chemotherapy management, 79.16% (DDS) and 94.31% (SDS) of Stem Cell Transplantation Management, 63.77% (DDS) and 87.37% (SDS) of Radiation therapy Management and 88.92% (DDS) and 85.86% (SDS) of Targeted therapy drugs management.

INDEX TERMS Leukemia, blood-producing, bone marrow, white blood cells, blood cancer, blood transfusion, pattern recognition, deep learning.

I. INTRODUCTION

Acute lymphoblastic leukemia (ALL) is a type of cancer that affects white blood cells and is the most common type of childhood cancer. Early detection and diagnosis of ALL are important for effective treatment. However, ALL symptoms can be difficult to recognize and may be mistaken for other illnesses [1]. To improve the accuracy and speed of diagnosis, pattern recognition technology can be used to identify changes in white blood cell count that may indicate the presence of ALL. Blood stem cells originate in the bone marrow, mainly in flat bones in adults (hip, sternum, skull, ribs, vertebrae, scapulae, to name a few.), and can follow two developmental lines [2]. Cells of the myeloid lineage give rise to white blood cells, especially neutrophil monocytes, platelets, and red blood cells; Cells of the lymphoid lining produce white blood cells, also called lymphocytes [3]. As a result of genetic changes and complex mechanisms that are not yet fully elucidated, stem cells can stop their growth prematurely or acquire the ability to replicate indefinitely

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and become resistant to the mechanisms of programmed cell death [4]. When this happens, the immature cells invade the marrow, blood, and sometimes the lymph nodes, spleen, and liver, forming leukemia [5]. One factor that characterizes the disease is the speed of its development: acute forms have a short or very short course and prevent cell maturation, while chronic forms have a slow evolution, in which the ability of marrow progenitors to mature. It is uncommon but maintained [6], [7]. Cancers affecting blood cells occur more often in childhood than in adolescence [8]. Specifically, acute lymphoblastic leukemia accounts for 14% of all leukemia diagnosed in people under 75, while acute myeloid leukemia accounts for 15–20% [9].

In adults, on the other hand, most acute leukemia's are myeloid form, while lymphoblastic leukemia accounts for less than 25-30% [10]. Chronic leukemia, however, is common in adults and rare in childhood. Although the incidence of leukemia is increasing, with almost 8,000 new cases diagnosed, mortality is decreasing due to continuous and steady improvements in treatment [11], [12]. In the early stages, chronic leukemia may not give any symptoms because the leukemic cells interfere with the functions of other cells in a limited way. In contrast to acute leukemia, symptoms occur early and can worsen very quickly [13], [14]. Fever, night sweats, tiredness and fatigue, headache, bone and joint pain, weight loss, and pallor are usually associated with red blood cell deficiency, thus a major anemic state [15]. If platelet deficiency occurs, small hemorrhages in the oral cavity or gastrointestinal tract or spots on the skin may appear [16]. Deep hemorrhages may appear in the brain or gastrointestinal tract at a later but always more rapid stage. When the white blood cell count is high, there may be persistent but well-tolerated fever-like symptoms like the worst flu syndrome [17]. Sometimes leukemic eruptions invade organs such as the stomach, intestines, kidneys, lungs, or nervous system, giving specific symptoms that indicate dysfunction of the organ involved [18]. In the last few years, there has been a steady and progressive improvement in the prognosis of the disease for two reasons: we know more about the underlying factors of these diseases, especially the genetic mutations associated with the more aggressive forms, and therefore can continue [19]. By transplanting in the early stages, when the patient is less compromised, fewer treatments and better results can be achieved, and constant improvement in combination therapies based on the characteristics of the individual patient's disease [20], [21].

Hematopoietic stem cell transplantation is one of the treatment options used to replace diseased cells, which have been destroyed by high doses of chemo or radiotherapy, with healthy ones from a compatible donor [22]. Often the donor is a sibling or family member, but it can also be a stranger with cells compatible with the patient's cells. In some cases, this approach can definitively cure leukemia, especially in young patients, and can be used for forms that no longer respond to chemotherapy [23]. This is why it is important to register in the bone marrow donor registry. A simple gesture, taking a small amount of blood or saliva for genetic typing, can save a life in the future. In addition to transplant surgery, other treatments today are chemotherapy combined with other approaches to stimulate the immune system to recognize and destroy leukemia cells [24], [25]. It targets leukemia cells and promotes their destruction by the immune system. An innovative treatment approach in recent years is immunotherapy with CAR-T cells, which are available for some leukemia that does not respond to conventional treatments [26]. In 2019, 61780 people were diagnosed with blood cancer. According to the National Cancer Institute, about 22,840 people will die. If acute leukemia is present, the disease may get worse quickly [27]. Alternatively, slowly progress to chronic leukemia that worsens over time. Symptoms are often caused by anemia [28]. The main contribution of this research paper is:

- Calculating prognostic patterns for patients with Acute Lymphoblastic Leukemia using highly accurate deep-learning methods
- Based on the calculated results, the analysis should be done to compare the accuracy of the results and recommend appropriate treatment methods for the patients.
- To prepare a detailed report on the severity of Acute Lymphoblastic Leukemia disease and its characteristics has to be classified based on the symptoms.

The remaining part of the paper has organized as the following. Section II provides elaborated information about the current research works, and Section III provides details about the proposed model and algorithm. Section IV expresses the analytical discussion about the proposed model. Section V provides the comparative analysis between the existing and proposed models, and finally, section VI provides the conclusion and future enhancements of the proposed model.

II. RELATED WORKS

Leukemia is a cancer of the blood and bone marrow. It is caused by abnormal production of certain blood cells due to malignancy. This causes disturbance in blood and immune system function. Due to this, there will be disruption in physical activities

A. ANALYSIS BASED ON DIAGNOSIS

Urbańska et al. [29] has discussed the hematologists and oncologists specialize in treating all. Doctors usually prefer a complete blood count (CBC) test to look for anything that can detect an abnormal white cell count. The 5-year survival rate for all diagnoses is over 90%. Bleeding gums, infections, fever, bone pain, fatigue are some of the signs and symptoms that a doctor should be consulted. Jamil et al. [30] has expressed before acute lymphocytic leukemia, your doctor will order blood tests, bone marrow tests, imaging tests, and spinal fluid tests. Treatment packages also include the cost of tests. Patients often need to stay in the hospital for 3 to 4 weeks throughout treatment. However, depending on the circumstances, many patients are able to leave the

hospital. Jiwani et al. [31] has discussed the first three months after treatment, doctors usually schedule follow-up appointments every few months for five years after treatment. If leukemia returns after treatment, it is referred to as recurrent or relapsed leukemia. Santos et al. [32] has expressed when this happens, a new testing cycle begins to understand as much as possible about the recurrence. After this exam, you and your doctor will discuss your treatment options. Chemotherapy is the primary treatment. However, depending on your subtype, you may receive alternative treatment.

Guo et al. [33] has expressed a targeted cancer drug, immunotherapy, or a stem cell or bone marrow transplant may be considered. In fact, in lymphoblastic leukemia's, when the cells involved are B and T lymphocytes, when they are transformed, called lymphoblast's, and myeloid progenitor cells, such as granulocytes and monocytes, are involved. Gupta et al. [34] has discussed another important classification concerns acute leukemia, which occurs more often in children and adolescents and is usually more aggressive and fast-moving and chronic forms, which mainly affect people in their 40s and 50s. Sekar et al. [35] has discussed an environmental factors, including exposure to ionizing radiation following or connected to diagnostic or therapeutic procedures, for example, associated with environmental pollution, for example, the famous case of the explosion at the Chernobyl nuclear power plant or chemical carcinogens, including benzene, benzopyrene, toxic aldehydes and some heavy metals.

Gupta et al. [36] has expressed a certain drugs used to treat cancer, especially when combined with radiotherapy, may increase the risk of 'secondary' leukemia; Genetic factors, such as having a family history of leukemia, other blood clots, or certain diseases, including Down's syndrome and Fanconi anemia, increase susceptibility to the disease due to changes in proteins involved in DNA repair processes. Khalil et al. [37] has discussed an acute lymphoblastic leukemia (ALL) is a type of cancer that begins in the bone marrow and white blood cells. It is the most common type of childhood cancer, accounting for about one-third of all childhood cancers. Wu et al. [38] has expressed an ALL is a serious and potentially life-threatening disease, but treatment has improved significantly in recent years and the overall prognosis is good. Risk factors for ALL include exposure to radiation, exposure to certain chemicals, genetic predisposition, and weakened immune systems. Exposure to radiation, either through medical treatments or through environmental sources such as nuclear radiation, increases the risk of ALL. Logeshwaran et al. [39] has exposure to certain chemicals, such as benzene and solvents, can also increase the risk. A family history of ALL also increases the risk of developing the disease. Finally, weakened immune systems, due to conditions such as HIV or AIDS, can increase the risk of ALL. The table 1 has provided the comprehensive analysis of the related works based on the diagnosis.

B. ANALYSIS BASED ON SYMPTOMS

Jiwani et al. [40] has provided the occasional fatigue is not a sign of leukemia. But it is always better to consult a doctor in case of physical fatigue. Some types of leukemia affect your production of red blood cells. These cells carry oxygen to all the cells in the body. So when there is a shortage of red blood cells you may experience shortness of breath. Rzepiel et al. [41] has identified the shortness of breath is also seen as a symptom of lung cancer. But patients with leukemia feel very tired. At the same time in rare cases they also suffer from shortness of breath. But there are many causes of shortness of breath. Even walking in the room is said to be difficult due to shortness of breath. Elsallab et al. [42] has discussed the bruising of the gums, intestines, lungs or head, abnormal bleeding are signs of low platelets and problems with blood clotting. These are severe symptoms of leukemia. Bleeding is caused by red spots appearing on the skin. This could be a sign of leukemia. It may not notice them because they are small dots and weak. These spots indicate low platelet levels in the blood. Masih et al. [43] has discussed the petechiae are usually found around the ankles. Because, body fluids stay in the feet throughout the day due to gravity. But petechiae can also be caused by a reaction to a drug or an infection. An increase in the size of the gums is called hyperplasia. These symptoms are usually only seen in a small number of people with acute leukemia. This is one of the most obvious leukemia symptoms.

Ziętara et al. [44] has expressed the acute leukemia causes fever or chills in the legs. But these events never occur in people with chronic leukemia. A person with leukemia may have a fever that lasts for more than 1 to 2 weeks. Zhong et al. [45] has identified the night sweats are a common symptom in leukemia patients. That would be a really bad sweat. This causes patients to become drenched in water. However, there are many causes of night sweats that are unrelated to cancer. Sinclair et al. [46] has identified the red blood cells supply oxygen to all cells in the body. The author says that when these cells are deficient, symptoms such as headaches can occur. Although this is not a common symptom, frequent headaches may be a symptom of leukemia-related anemia. Gupta et al. [47] has expressed the abnormal pallor, such as headache, fatigue, and shortness of breath, may be symptoms of anemia in acute and some chronic leukemia patients. ''If they're very pale, it means they're more susceptible to leukemia. And they are sick''. They always feel tired. If your red blood cell count is low enough to be pale, you will have more congestion. But if your skin is dark then it can be difficult to detect. But it can affect the eyelids and inner lining. This pale color can also be a deficiency of vitamin B12.

Mizuki et al. [48] has expressed a relatively uncommon symptom, pain in the bones is a symptom of chronic and acute leukemia. So it is better to consult your doctor if you feel constant pain in your bones ranging from mild to severe pain. A lymph test is one of the tests you should have regularly. Giebel et al. [49] has discussed there will

TABLE 1. Comprehensive analysis based on the diagnosis.

Authors	Research Highlights
Urbańska, Z.,et al.[29]	Doctors usually prefer a complete blood count (CBC) test to look for anything that can detect an abnormal white cell count. The 5-year survival rate for all diagnoses is over 90%.
Jamil, S. F.,et al.[30]	The patients often need to stay in the hospital for 3 to 4 weeks throughout treatment. However, depending on the circumstances, many patients are able to leave the hospital
Jiwani, N.,et al.[31]	The first three months after treatment, doctors usually schedule follow-up appointments every few months for five years after treatment. If leukemia returns after treatment, it is referred to as recurrent or relapsed leukemia
Santos, M. M. D.,et al.[32]	After the test, the doctor will discuss your treatment options. Chemotherapy is the primary treatment. However, depending on your subtype, you may receive alternative treatment
Guo, M.,et al.[33]	In lymphoblastic leukemia's, when the cells involved are B and T lymphocytes, when they are transformed, called lymphoblast's, and myeloid progenitor cells
Gupta, D. G.,et al.[34]	This disease occurs more often in children and adolescents and is usually more aggressive and fast-moving and chronic forms, which mainly affect people in their 40s and 50s
Sekar, G.,et al.[35]	An environmental factors, including exposure to ionizing radiation following or connected to diagnostic or therapeutic procedures
Gupta, S.,et al.[36]	The genetic factors, such as having a family history of leukemia, other blood clots, or certain diseases, including Down's syndrome and Fanconi anemia
Khalil, M.,et al.[37]	An acute lymphoblastic leukemia (ALL) is a type of cancer that begins in the bone marrow and white blood cells. It is the most common type of childhood cancer, accounting for about one-third of all childhood cancers
Wu, Y.,et al.[38]	An ALL is a serious and potentially life-threatening disease, but treatment has improved significantly in recent years and the overall prognosis is good. Exposure to radiation, either through medical treatments or through environmental sources such as nuclear radiation, increases the risk of ALL
Logeshwaran, J.,et al.[39]	A family history of ALL also increases the risk of developing the disease. Finally, weakened immune systems, due to conditions such as HIV or AIDS, can increase the risk of ALL

be significant painless swelling in your lymph nodes. It can check your neck, armpits and groin area to check for this. It is normal for the lymph nodes to go up and down during times of infection or inflammation. Songthawee et al. [50] has discussed if they are large or keep growing, it could be one of the symptoms of leukemia or lymphoma. About 1 in 20 leukemia patients may have a skin rash. They occur in two types. A rash caused by Sweet's syndrome is seen as a sign of blood cancer. Leukemia looks like a lump in the skin. And the rashes caused by Sweet's disease, allergies in any form, have a common resemblance to the rashes caused by leukemia. They continue to grow and spread. The table 2 has provided the comprehensive analysis of the related works based on the symptoms.

From the table 1 and table 2, the following issues were identified,

- People with leukemia don't go away even if it's just a little bit. No matter how many antimicrobials doctors prescribe, it won't work. A complete blood count may be done to check for changes in your white blood cell, hemoglobin and platelet levels.
- An abnormal reduction in white blood cells weakens the immune system. This leads to frequent infections and the feeling of being sick all the time. If you have this symptom along with other symptoms such as fatigue or bruising, it is best to consult your doctor.
- Leukemia always sneaks up on your body first. Symptoms in leukemia patients are common symptoms of other diseases. So a physical exam, blood test and a bone marrow biopsy may be done. Through this, doctors can accurately know the level of leukemia in the body.

The main novelty is to provide the optimal solution of the above mentioned problems.

- It is important to be aware of the risk factors for ALL and to take steps to reduce the risk. This can include avoiding exposure to radiation, limiting the use of certain chemicals, and maintaining a healthy lifestyle with a strong immune system.
- While risk factors for ALL cannot be completely eliminated, understanding them can help to reduce the chances of developing the disease.

TABLE 2. Comprehensive analysis based on the symptoms.

Authors	Research Highlights
Jiwani, N.,et al.[40]	Some types of leukemia affect your production of red blood cells. These cells carry oxygen to all the cells in the body. So when there is a shortage of red blood cells you may experience shortness of breath
Rzepiel, A.,et al.[41]	The patients with leukemia feel very tired. At the same time in rare cases they also suffer from shortness of breath. But there are many causes of shortness of breath. Even walking in the room is said to be difficult due to shortness of breath
Elsallab, M.,et al.[42]	The abnormal bleeding are signs of low platelets and problems with blood clotting. These are severe symptoms of leukemia. Bleeding is caused by red spots appearing on the skin. This could be a sign of leukemia. It may not notice them because they are small dots and weak
Masih, K. E., et al.[43]	The body fluids stay in the feet throughout the day due to gravity. But petechiae can also be caused by a reaction to a drug or an infection. An increase in the size of the gums is called hyperplasia. These symptoms are usually only seen in a small number of people with acute leukemia
Ziętara, K. J.,et al.[44]	The acute leukemia causes fever or chills in the legs. But these events never occur in people with chronic leukemia. A person with leukemia may have a fever that lasts for more than 1 to 2 weeks
Zhong, C.,et al.[45]	The night sweats are a common symptom in leukemia patients. That would be a really bad sweat. This causes patients to become drenched in water
Sinclair, P. B., et al.[46]	The red blood cells supply oxygen to all cells in the body. The author says that when these cells are deficient, symptoms such as headaches can occur
Gupta, K., et al.[47]	If your red blood cell count is low enough to be pale, you will have more congestion. But if your skin is dark then it can be difficult to detect. But it can affect the eyelids and inner lining. This pale color can also be a deficiency of vitamin B12
Mizuki, K.,et al.[48]	A relatively uncommon symptom, pain in the bones is a symptom of chronic and acute leukemia. So it is better to consult your doctor if you feel constant pain in your bones ranging from mild to severe pain.
Giebel, S.,et al.[49]	There will be significant painless swelling in your lymph nodes. It can check your neck, armpits and groin area to check for this
Songthawee, N.,et al.[50]	A rash caused by Sweet's syndrome is seen as a sign of blood cancer. Leukemia looks like a lump in the skin. And the rashes caused by Sweet's disease, allergies in any form, have a common resemblance to the rashes caused by leukemia

- Leukemia symptoms include unexplained lesions that do not cause any damage to the body. An unusual injury can cause low platelets or other blood clotting problems. These injuries can occur anywhere. But they usually occur in the hands and feet.

An improved algorithm based on deep learning is developed based on which the severity of Acute Lymphoblastic Leukemia is calculated, analyzed, and finally, classification tasks are developed. It is based on the pattern recognition method.

III. PROPOSED MODEL

With pattern recognition technology, the diagnosis of ALL can be much faster and more accurate than traditional methods. For example, traditional methods rely heavily on manual counting and analysis of white blood cells, which can be time consuming and prone to human error. However, with pattern recognition technology, a computer can quickly and accurately recognize patterns in the data that indicate the presence of ALL. This can lead to a faster and more accurate diagnosis, which can help ensure that patients receive the best possible treatment as soon as possible. The proposed model has the following block diagram in fig.1.

A. SYMPTOMS DATASET

Symptoms of acute leukemia in children appear early when the white blood cell count rises sharply. Early detection of leukemia improves the success rate of treatment. Common symptoms of leukemia in children include:

- Persistent infection and fever
- Enlarged lymph nodes
- Anemia and wheezing
- Frequent runny nose
- Bleeding or sore gums
- Easy bruising and abdominal swelling
- Bone or joint pain

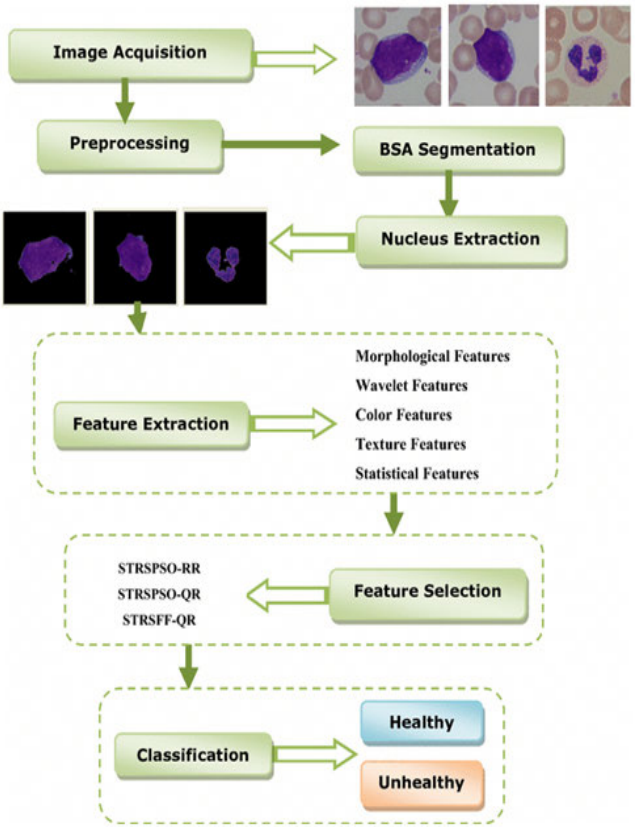

FIGURE 1. Proposed block diagram.

- Anorexia and Seizure
- Swelling of the face, neck and arms

In leukemia, blood cancer cells are derived from hematopoietic stem cells, from which all corpuscular components of blood normally originate: red blood cells, platelets, and white blood cells, including lymphocytes and granulocytes.

B. PREPROCESSING

The use of computational deep learning for the detection of acute lymphoblastic leukemia (ALL) is a relatively new approach. In order to make this approach more efficient and accurate, pre-processing of the data is necessary. The pre-processing of the data can be done in various ways, such as the normalization of the data, feature selection, feature extraction and dimensionality reduction.

C. NORMALIZATION

Normalization is the process of scaling the data to a specific range, such as 0 to 1, so that all the features are on the same scale. This helps the algorithm to learn the patterns better as it can focus on the differences between the features instead of being overwhelmed by the magnitude of the features

D. FEATURE SELECTION

Feature selection is the process of selecting the most relevant features that are necessary for the task. Different techniques can be used for feature selection, such as mutual information and correlation-based feature selection. This can be done using techniques such as Principal Component Analysis (PCA) and Singular Value Decomposition (SVD). Using a combination of these techniques, it is possible to reduce the number of features while preserving their information content. This will result in more accurate and efficient models for the detection of ALL.

E. FEATURE EXTRACTION

Feature extraction is the process of transforming the input features into a new set of features that are more suitable for the task. It can be done using techniques such as Principal Component Analysis (PCA) and Non-Negative Matrix Factorization (NMF). Dimensionality reduction is the process of reducing the number of features by removing the redundant and irrelevant. Once the features have been extracted, they can be used to identify patterns in the data that may be indicative of ALL. For example, the deep learning algorithm may be able to detect patterns in the data that suggest the presence of the disease, even if the individual symptoms are not present. This could help to speed up the diagnosis process and ensure that patients receive the correct treatment in a timely manner.

F. CLASSIFICATION

Anemia, thrombocytopenia, or pancytopenias, especially the latter stage, are sufficient to raise suspicion of a leukemic state. As mentioned, the basic test is a blood count followed by a microscopic reading of a peripheral blood smear more in-depth diagnostics such as immunophenotyping; ALL is classified into two categories:

- B-cell: B-cell ALL is the most common type in adults. B-cell ALL is a fast-growing cancer that starts in the bone marrow and can spread to other parts of the body. Symptoms of B-cell ALL can include fatigue, weight loss, anemia, night sweats, fever, and bone pain
- T-cell: T-cell ALL is more common in children. In T-cell ALL, the cancer starts in the thymus and can spread to other parts of the body. Symptoms of T-cell ALL can include fever, weight loss, anemia, and joint pain.

The cytogenetic analysis (study of chromosomes) and bone marrow biopsy, which allows a bone marrow sample to be obtained from the back of the iliac bone. This test is of fundamental importance in diagnosing the type of leukemia and, therefore, the treatment strategy to control this pathology.

G. DETECTION

Acute Lymphoblastic Leukemia (ALL) is a type of cancer that affects the white blood cells, which are responsible for fighting infection. Clinical identification methods for ALL include physical examination, laboratory tests, imaging studies, and biopsy.

- Physical Examination: A physical examination will be conducted to check for signs of ALL, such as swollen

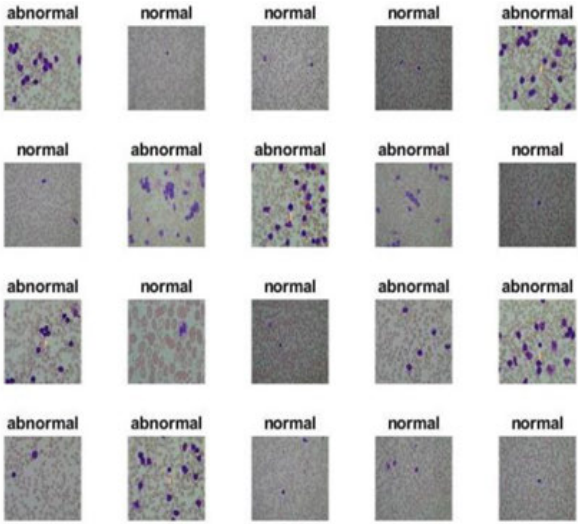

FIGURE 2. General diagnosis based dataset.

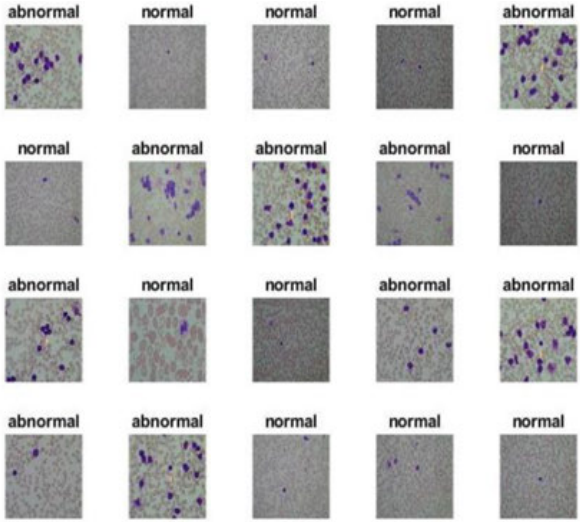

FIGURE 3. Symptoms based dataset.

lymph nodes, fever, fatigue, and easy bruising and bleeding.

- Laboratory Tests: A complete blood count and blood chemistry tests will be conducted to check for abnormal levels of white blood cells, red blood cells, and platelets. In addition, a leukemia marker test may be performed to look for leukemia cells in the blood.
- Imaging Studies: Imaging studies such as X-rays, CT scans, and MRI scans may be used to look for enlarged organs and tumors.
- Biopsy: A sample of the affected tissue may be taken and examined under a microscope to confirm the diagnosis of ALL. This will also allow the doctor to determine the type and severity of the disease.

These are the most common clinical identification methods used to diagnose ALL. The doctor will determine the best course of treatment based on the results of these tests.

IV. ANALYTICAL DISCUSSIONS

Acute lymphoblastic leukemia (ALL) is a type of cancer that affects the white blood cells in the body. It is a serious and potentially fatal illness that requires prompt and aggressive treatment. The diagnosis of ALL can be difficult due to its complexity and the wide range of symptoms it may present. Fortunately, computational deep learning techniques have been developed to help with the diagnosis of this disease. The fig 2 demonstrates the general diagnosis based dataset,

$$A(x) = \frac{1}{S}\sum_{c=0}^{s-1} b(x-c) + \frac{1}{D}\sum_{z=0}^{D-1} c(x-z) \tag{1}$$

where, A(x) is the present input samples, b(x-c) is the past diagnosis based input samples, c(x-z) is the past symptoms based input samples. S is the number of disease identification pixel in diagnosis based samples and D is the number of disease identification pixel in symptoms based samples. Now we need to detect the edges of the Leukemia cells with the help of laplacian filter,

$$\alpha^2 r = \frac{\partial^2 r}{\partial^2 x} + \frac{\partial^2 r}{\partial^2 y} \tag{2}$$

where, $\alpha^2 r$ represents the second order differential equation and x,y are the binary matrix coordinates of the samples. Now we obtained the enhanced quality samples from the eq.3

$$E(H) = A(x) - \alpha^2 r \tag{3}$$

Accumulation of one or more mutations in the genetic makeup of this cell produces clones of malignant, mature, and dysfunctional cells that proliferate in the bone marrow. The fig 3 demonstrates the symptoms based dataset, Sometimes, tumor blasts accumulate in the central nervous system, causing vomiting, headache, and confusion, or in other organs (such as the liver, testicles, lungs, and bones); in other cases, the disease may be completely asymptomatic and only incidentally detected routine tests. Deep learning techniques use multi-layered neural networks to extract patterns and features from data sets. The fig 4 explains the Pattern Recognition analysis.

The proposed deep learning model has been used to identify Acute Lymphoblastic Leukemia (ALL) in medical imaging. Deep learning can be used to build models that analyze medical images and detect the presence of cancer. It can also be used to identify other features in the image, such as the tumor's size, shape, and intensity. The deep learning models can then classify the images as malignant or benign. It can help doctors make more accurate diagnoses and provide better patient treatment options. Deep learning can also be used to identify relevant biomarkers and determine the aggressiveness of the disease. The deep learning models can be trained on large datasets of medical images to improve accuracy and reduce false positives.

This type of learning is especially useful for medical applications, as it can help to identify subtle patterns in data that may be invisible to the human eye. In the case

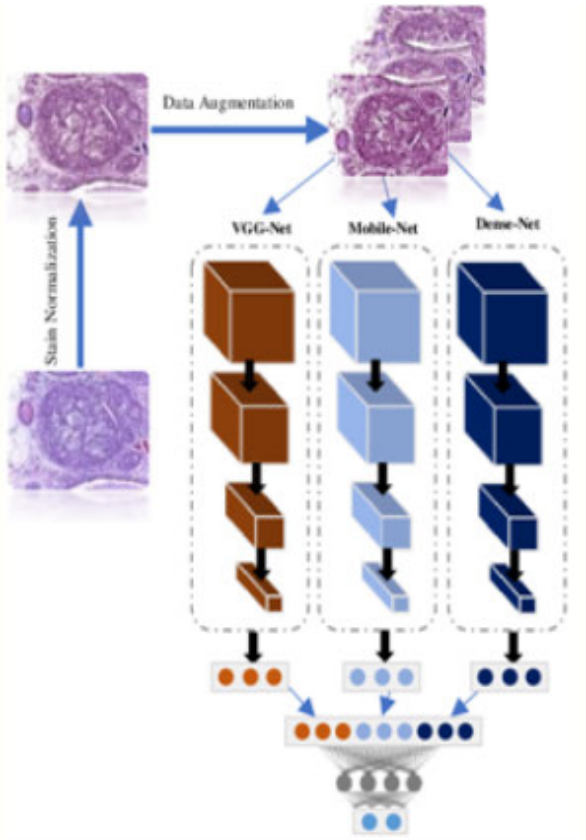

FIGURE 4. Pattern recognition analysis.

of ALL, deep learning can be used to extract features from data sets of patient samples, such as blood tests, imaging scans and genetic markers. In cases of disease recurrence, bone marrow transplantation may be used, in which the patient is given an overdose of chemo/radiotherapy aimed at suppressing hemopoiesis, followed by infusion of compatible or incompatible stem cells.

- Induction: aims to temporarily or permanently stop the evolution of the disease and symptoms and eliminate leukemic cells through drug combinations;
- Maintenance: Once remission is achieved, the aim is to keep the patient in as complete remission as possible with a regimen that aims to kill any remaining leukemic cells not removed by induction therapy;
- Supportive care: Aims to relieve the symptoms of leukemia, improve quality of life, and help the patient cope with the toxicity of chemotherapy

The fig.5 expresses the Different stages in Leukemia. It should be treated as soon as possible to increase the chance of remission. The main treatment is chemotherapy, which is used to destroy the lesions and prevent them from growing. Corticosteroids are the best combination therapy in cases of lymphoblastic leukemia. Radiotherapy plays a minor role and is often relegated to certain cases. Treatment of leukemia in children depends on the type of leukemia and other factors such as age at diagnosis, gender, and initial white blood cell

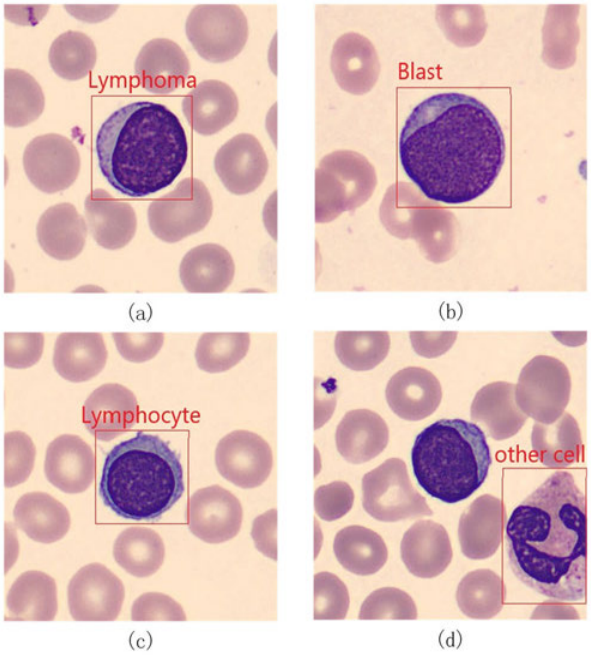

FIGURE 5. Different stages in Leukemia; a) Lymphoma; b) Blast; c) Lymphocyte; d) Other cell.

count. Cross-validation is a technique used to evaluate the model's performance on unseen data. It involves splitting the data into a training set, a validation set, and a test set. The model is then trained on the training set and evaluated on the validation set. The model that performs best on the validation set is selected and tested on the unseen test set.

V. COMPARATIVE ANALYSIS

The proposed Acute Lymphoblastic Leukemia detection model (ALLDM) has compared with the existing Machine Learning in Detecting Early-Stage Leukemia (MLD-ESL) and Optimized Deep Neuro-Fuzzy Network with MapPeduce Architecture (ODNFN). Here the MATLAB (r2022a) is the tool used to execute the results.

A. CHEMOTHERAPY MANAGEMENT (CHM)

It is the mainstay of treatment for leukemia in children. A single drug or combination of anticancer drugs is administered through an IV line, taken orally, or injected into a muscle. Chemotherapy is done in cycles, with each cycle followed by a break. For acute myeloid leukemia's, high-dose chemotherapy is usually given for a short period of a few months. For acute lymphocytic leukemia's, lower doses of chemotherapy are usually administered for longer periods of two years or longer. The table 3 provides the comparison of Chemotherapy Management between the existing MLD-ESL, ODNFN models and proposed ALLDM models. The DDS indicates the diagnosis dataset and SDS indicates the symptoms dataset.

The fig.6 demonstrates the comparison of chemotherapy management. In a comparison range the proposed ALLDM model achieved 81.53% (DDS) and 87.92% (SDS) of

TABLE 3. Comparison of chemotherapy management (in %).

No.of Samples	MLD-ESL (DDS)	MLD-ESL (SDS)	ODNFN (DDS)	ODNFN (SDS)	ALLDM (DDS)	ALLDM (SDS)
100	77.23	70.48	61.495	88.24	92.36	98.81
200	74.25	67.50	58.515	77.23	81.35	87.80
300	65.84	59.09	50.105	65.25	69.37	75.82
400	45.25	38.50	29.515	45.66	79.78	76.23
500	32.22	25.47	16.485	36.84	70.96	77.41
600	55.47	48.72	39.735	77.41	81.53	87.98
700	66.84	60.09	51.105	88.23	92.35	98.80
800	38.25	31.50	22.515	84.21	88.33	94.78
900	65.84	59.09	50.105	80.12	84.24	90.69
1000	77.45	70.70	61.715	77.65	81.77	88.22

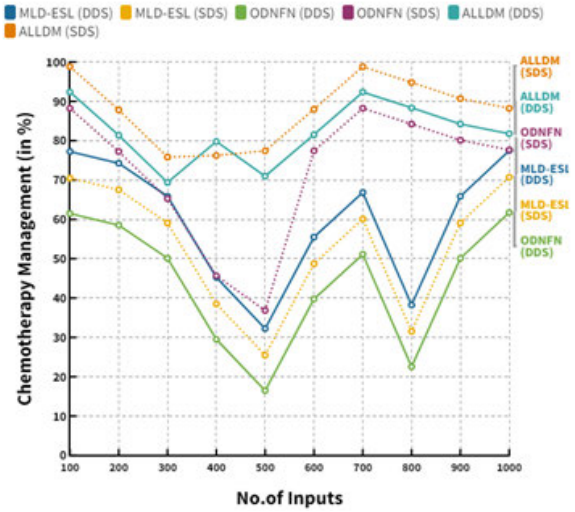

FIGURE 6. Comparison of chemotherapy management.

chemotherapy management. Meanwhile the existing models reached MLD-ESL obtained 55.47% (DDS) and 48.73% (SDS); and ODNFN reached 39.74% (DDS) and 77.41% (SDS) of chemotherapy management respectively.

B. STEM CELL TRANSPLANTATION MANAGEMENT (SCTM)

After chemotherapy destroys the bone marrow and the cancer cells in it, brand new stem cells from a donor can be transplanted into the bone marrow to restore blood cell formation. Donor bone marrow cells from a sibling, twin (related and tissue-matched) or stem cell-rich baby's umbilical cord blood (unrelated-matched). A bone marrow transplant allows the child to receive higher doses of chemotherapy. A bone marrow transplant or a stem cell transplant may improve the chances of a cure. The table 4 provides the comparison of Stem Cell Transplantation Management between the existing MLD-ESL, ODNFN models and proposed ALLDM models.

The fig.7 demonstrates the comparison of Stem Cell Transplantation Management. In a comparison range the proposed ALLDM model achieved 79.16% (DDS) and 94.31% (SDS) of Stem Cell Transplantation Management. Meanwhile the existing models reached MLD-ESL obtained 61.27% (DDS) and 66.10% (SDS); and ODNFN reached 45.12% (DDS) and 60.66% (SDS) of Stem Cell Transplantation Management.

TABLE 4. Comparison of stem cell transplantation management (in %).

No.of Samples	MLD-ESL (DDS)	MLD-ESL (SDS)	ODNFN (DDS)	ODNFN (SDS)	ALLDM (DDS)	ALLDM (SDS)
100	70.79	77.53	54.29	60.67	79.17	94.32
200	68.06	74.26	51.66	53.10	69.73	83.81
300	60.35	65.00	44.24	44.86	59.46	72.38
400	41.48	42.36	26.06	31.39	42.67	73.68
500	29.54	28.02	14.55	25.33	35.11	75.26
600	50.85	53.60	35.08	53.22	69.88	83.98
700	61.27	66.10	45.12	60.66	79.16	94.31
800	35.06	34.66	19.88	57.89	75.71	90.47
900	60.35	65.00	44.24	55.08	72.21	86.57
1000	71.00	77.78	54.49	53.38	70.09	84.21

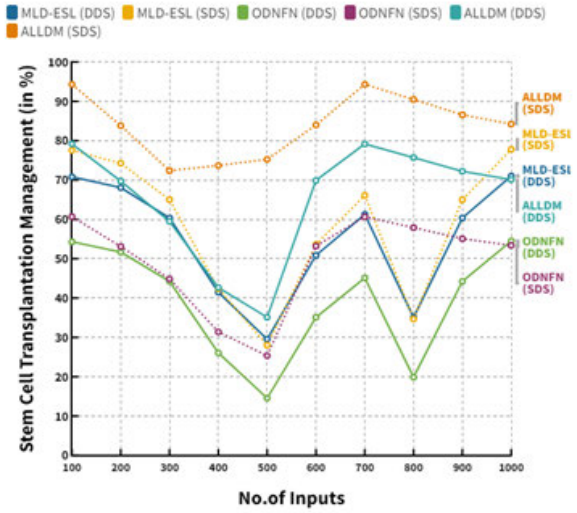

FIGURE 7. Comparison of stem cell transplantation management.

TABLE 5. Comparison of radiation therapy management (in %).

No.of Samples	MLD-ESL (DDS)	MLD-ESL (SDS)	ODNFN (DDS)	ODNFN (SDS)	ALLDM (DDS)	ALLDM (SDS)
100	73.32	74.34	57.70	68.41	70.02	84.87
200	71.82	73.37	56.51	66.92	68.36	83.73
300	71.38	55.37	54.90	64.91	66.13	62.54
400	70.24	53.84	65.74	58.43	81.18	60.74
500	76.94	48.14	64.95	57.44	80.08	74.03
600	75.34	46.49	64.16	76.46	78.99	72.09
700	73.20	51.98	63.37	75.47	77.89	78.55
800	71.42	50.98	53.20	62.79	63.77	87.37
900	51.72	57.03	52.71	62.18	63.09	74.49
1000	49.99	55.97	51.82	61.07	61.85	73.24

C. RADIATION THERAPY MANAGEMENT (RTM)

Radiation therapy refers to treatment in which high-energy radiation is used to destroy cancer cells. It is not the preferred treatment option for childhood leukemia, but may be useful before bone marrow transplantation. It can be used to prevent leukemia from spreading to other parts of the body. The table 5 provides the comparison of Radiation therapy Management between the existing MLD-ESL, ODNFN models and proposed ALLDM models.

The fig.8 demonstrates the comparison of Radiation therapy Management. In a comparison range the proposed

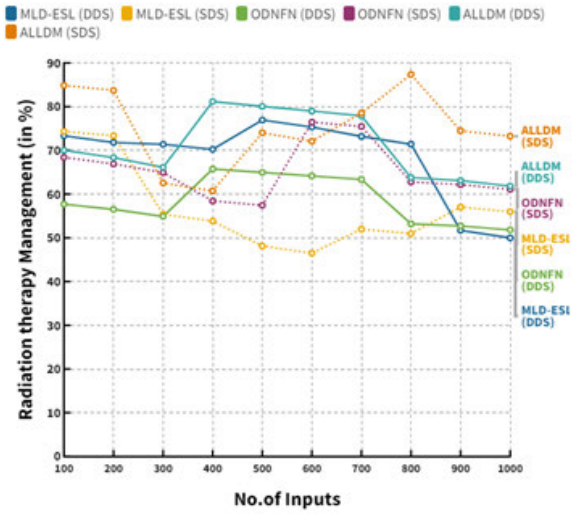

FIGURE 8. Comparison of radiation therapy management.

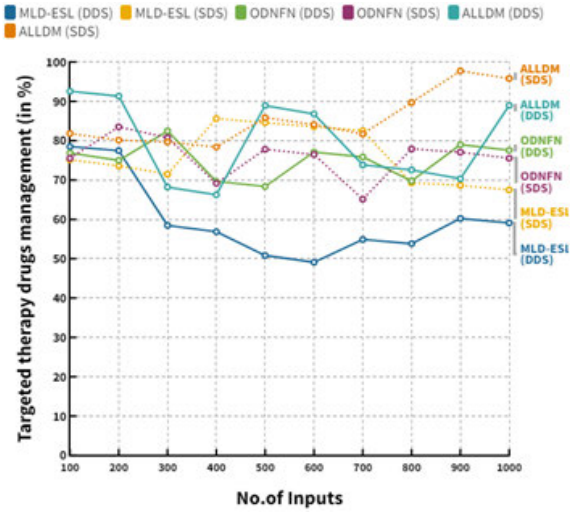

FIGURE 9. Comparison of targeted therapy drugs management.

TABLE 6. Comparison of targeted therapy drugs management (in %).

No.of Samples	MLD-ESL (DDS)	MLD-ESL (SDS)	ODNFN (DDS)	ODNFN (SDS)	ALLDM (DDS)	ALLDM (SDS)
100	78.49	75.14	76.89	75.52	92.55	81.82
200	77.47	73.59	74.99	83.50	91.31	80.15
300	58.46	71.49	82.45	80.77	68.20	79.66
400	56.85	85.61	69.62	69.15	66.24	78.38
500	50.83	84.58	68.36	77.81	88.92	85.86
600	49.09	83.55	77.11	76.47	86.80	84.08
700	54.88	82.52	75.86	65.13	73.85	81.68
800	53.82	69.28	69.76	77.89	72.56	89.70
900	60.21	68.64	78.98	77.06	70.33	97.72
1000	59.09	67.48	77.57	75.54	88.96	95.78

ALLDM model achieved 63.77% (DDS) and 87.37% (SDS) of Radiation therapy Management. Meanwhile the existing models reached MLD-ESL obtained 71.42% (DDS) and 50.98% (SDS); and ODNFN reached 53.20% (DDS) and 62.79% (SDS) of Radiation therapy Management respectively.

D. TARGETED THERAPY DRUGS MANAGEMENT (TTDM)

These are new drugs that target specific areas of cancer cells. For example, some drugs are designed to control chromosomal gene mutations in cancer cells and slow their growth. It's too early to tell if these drugs can cure childhood leukemia, but in the long term they slow and control the disease's progression. The table 6 provides the comparison of Targeted therapy drugs management between the existing MLD-ESL, ODNFN models and proposed ALLDM models.

The fig.9 demonstrates the comparison of Targeted therapy drugs management. In a comparison range the proposed ALLDM model achieved 88.92% (DDS) and 85.86% (SDS) of Targeted therapy drugs management. Meanwhile the existing models reached MLD-ESL obtained 50.83% (DDS) and 84.58% (SDS); and ODNFN reached 68.36% (DDS) and 77.81% (SDS) of Targeted therapy drugs management respectively.

TABLE 7. Comparison of radiation therapy management (in %).

Parameters	MLD-ESL (DDS)	MLD-ESL (SDS)	ODNFN (DDS)	ODNFN (SDS)	ALLDM (DDS)	ALLDM (SDS)
CHM	55.47	48.72	39.73	77.41	81.53	87.98
SCTM	61.27	66.10	45.12	60.66	79.16	94.31
RTM	71.42	50.98	53.20	62.79	63.77	87.37
TTDM	50.83	84.58	68.36	77.81	88.92	85.86
CHM	55.47	48.72	39.73	77.41	81.53	87.98

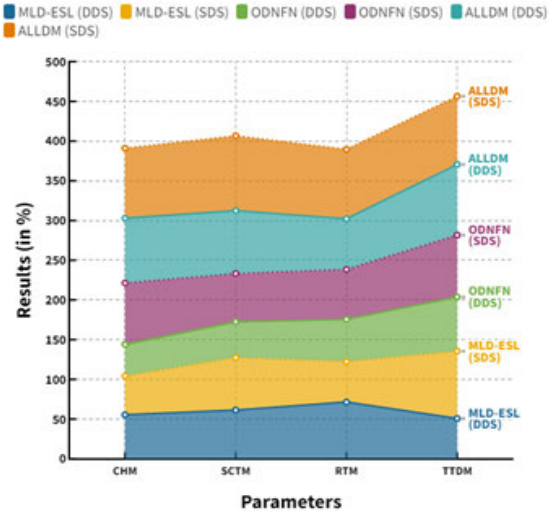

FIGURE 10. Overall performance comparison.

The table 7 shows the overall performance comparison.

The fig.10 provides the overall comparison between the existing and proposed models. In saturation tip the proposed ALLDM model achieved 81.53% (DDS) and 87.92% (SDS) of chemotherapy management, 79.16% (DDS) and 94.31% (SDS) of Stem Cell Transplantation Management, 63.77% (DDS) and 87.37% (SDS) of Radiation therapy Management and 88.92% (DDS) and 85.86% (SDS) of Targeted therapy drugs management. Targeted therapy drugs may be used

FIGURE 11. Robustness of proposed model.

TABLE 8. Robustness of proposed model (in %).

Parameters	MLD-ESL (DDS)	MLD-ESL (SDS)	ODNFN (DDS)	ODNFN (SDS)	ALLDM (DDS)	ALLDM (SDS)
Accuracy	66.88	72.56	84.25	83.54	92.58	95.68
Precision	65.14	70.58	83.65	85.54	91.44	92.03
Recall	74.58	75.29	79.99	81.56	94.25	96.68
F1-score	91.45	86.65	85.45	81.68	93.54	94.58

with chemotherapy or instead of chemotherapy. A reduction in red blood cells may be the main reason for this. This leads to physical exhaustion. In chronic and severe days this fatigue and physical weakness may be greater. But these symptoms worsen over time. The robustness of proposed Acute Lymphoblastic Leukemia detection model (ALLDM) can be measured by its ability to accurately classify ALL cases and reduce the number of false positives and false negatives. It can be done by evaluating the model's performance on a separate test dataset and assessing its accuracy, precision, recall, and F1 score shown in the fi.11. Additionally, the model should be tested on various datasets to ensure it is robust to different data types. Furthermore, the model should be tested on cases with different levels of severity and on cases from different populations to ensure that it is balanced for all groups. By evaluating these factors, the robustness of an ALL detection model can be determined and express in the table 8.

The scalability of deep learning models for detecting Acute Lymphoblastic Leukemia (ALL) depends on data availability and compute resources. The more available data and computing resources, the more accurate a deep learning model can be in detecting ALL. Additionally, the use of transfer learning, where a model is pre-trained on a related task and then fine-tuned for ALL detection, can significantly improve the model's scalability. Finally, careful architecture design and hyper parameter tuning can help ensure that the model can scale efficiently.

VI. CONCLUSION

Acute lymphoblastic leukemia (ALL) is a type of cancer of the blood and bone marrow that is characterized by an increased and abnormal production of immature lymphocytes, or white blood cells. It is the most common type of cancer in children and occurs in adults as well. CAR-T cells are the patient's own T lymphocytes that have been genetically modified to be fitted with a CAR molecule. Once they are reintroduced into the patient, CAR-T cells can specifically recognize tumor cells and effectively attack and destroy them. the proposed ALLDM model achieved 81.53% (DDS) and 87.92% (SDS) of chemotherapy management, 79.16% (DDS) and 94.31% (SDS) of Stem Cell Transplantation Management, 63.77% (DDS) and 87.37% (SDS) of Radiation therapy Management and 88.92% (DDS) and 85.86% (SDS) of Targeted therapy drugs management. Treatment for ALL is highly individualized and depends on the type of leukemia, the stage of the disease, and the patient's age and overall health. Treatment may involve chemotherapy, radiation therapy, stem cell transplant, or a combination of these treatments. Surgery may be used to remove any tumors that may have developed. The prognosis for ALL depends on a variety of factors, such as the type and stage of the cancer, the age of the patient, and the response to treatment. With appropriate treatment and timely follow-up care, many patients can achieve complete remission.

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