International Journal of Engineering Technology and Management Sciences
Website: ijetms.in Issue: 2 Volume No.9 March - April – 2025
DOI:10.46647/ijetms.2025.v09i02.021 ISSN: 2581-4621

Predicting Bone Marrow Transplantation Outcomes Using Decision Trees: A Supervised Learning Approach

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Abstract
Bone marrow transplantation (BMT) is a critical therapeutic intervention for patients with hematological malignancies and other life-threatening disorders. Accurately predicting the outcomes of BMT is essential for improving patient care, optimizing treatment strategies, and managing post-transplantation risks. In this study, we present a supervised learning approach using decision trees to predict the outcomes of bone marrow transplantation based on clinical and demographic data. We collected data from patients who underwent bone marrow transplantation, including variables such as age, gender, disease type, donor type, pre-transplant health indicators, and post-transplant complications. Decision trees, a widely used machine learning algorithm, were employed to build predictive models. These models aim to identify key factors that influence transplantation success, such as survival rate, disease relapse, graft-versus-host disease (GVHD) occurrence, and long-term patient health outcomes.
Our results demonstrate that decision trees can effectively classify patients into outcome categories with reasonable accuracy. Important predictors identified include patient age, donor compatibility, and specific pre-transplant health conditions. By providing interpretable decision paths, the model aids clinicians in understanding the risk factors associated with poor or favorable outcomes. Moreover, the decision tree approach allows for personalized predictions, supporting more tailored patient care.
Keywords: - Bone marrow transplantation, decision trees, supervised learning, predictive modeling, patient outcomes.

1. Introduction

Bone marrow transplantation (BMT) [1] has become a life-saving treatment option for patients with hematological disorders, such as leukemia, lymphoma, and aplastic anemia. Despite its therapeutic potential, BMT is a complex procedure with significant risks, including infection, graft-versus-host disease (GVHD) [2], and relapse of the underlying condition. Accurate prediction of BMT outcomes is critical for improving treatment planning, managing potential complications, and ultimately enhancing patient survival. Several factors influence the success of BMT, including patient demographics (age, gender), disease characteristics, pre-transplant health, donor compatibility, and post-transplant care. Traditionally, clinicians have relied on clinical experience and statistical models to estimate transplantation outcomes. However, such approaches often fail to capture the complexity and interactions between the numerous variables that affect patient prognosis.

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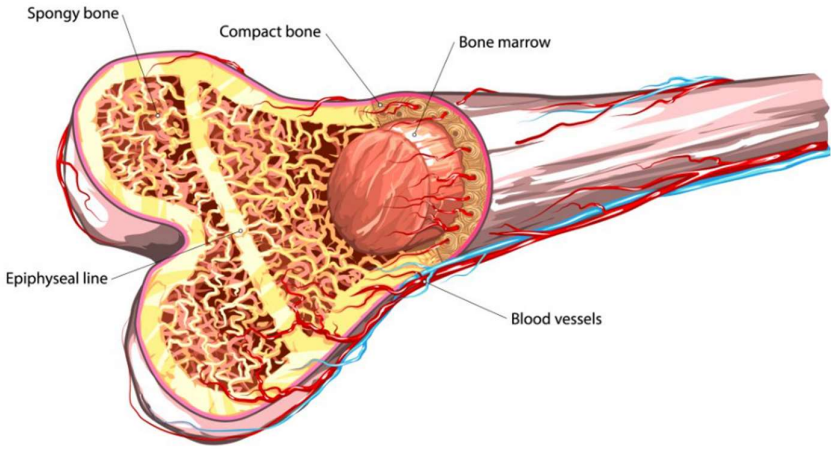

Fig-1: Structure of Bone marrow

Recent advancements in machine learning [11], particularly in the area of supervised learning [3], offer new opportunities for improving predictive models in medical decision-making. Decision trees, a widely-used supervised learning algorithm, provide a transparent and interpretable approach for modeling complex relationships between variables. Unlike traditional models, decision trees can handle both categorical and continuous data, making them well-suited for analyzing diverse clinical datasets. Additionally, decision trees produce easily interpretable rules, which can aid in understanding the factors driving successful or poor outcomes.

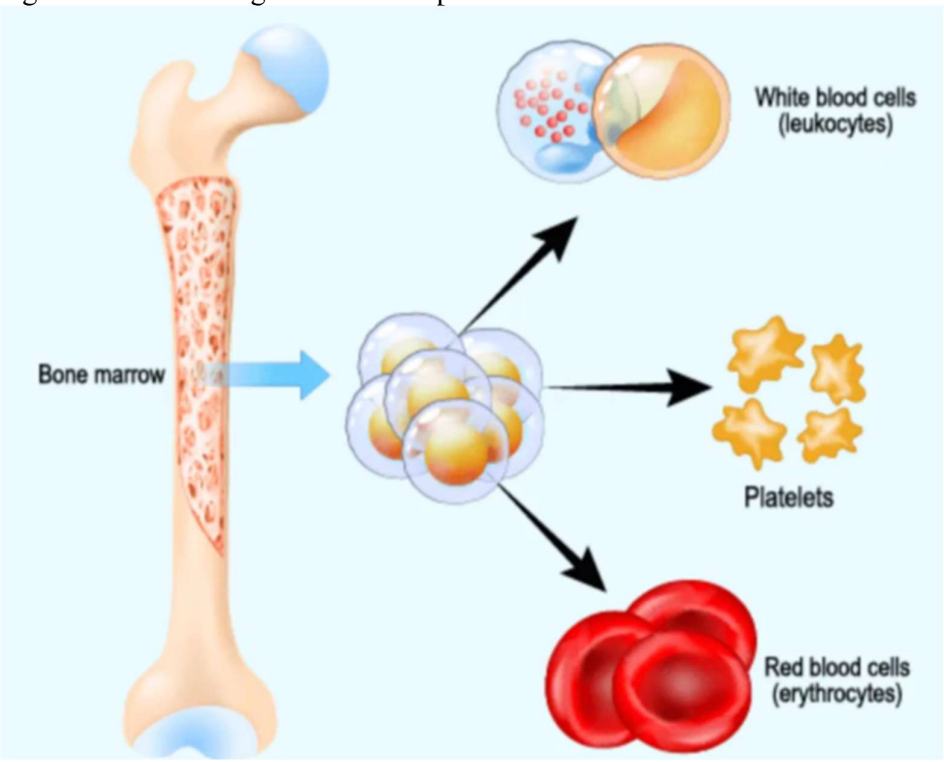

Fig-2: Bone Marrow Transplantation.

In this proposal, we propose the use of decision trees to predict the outcomes of bone marrow transplantation. By analyzing clinical and demographic data, we aim to identify key factors associated with transplantation success or failure. The decision tree algorithm allows for personalized predictions based on patient-specific characteristics, supporting individualized treatment strategies.

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Furthermore, the model's interpretability provides valuable insights for clinicians, helping them make informed decisions about patient care.

1.1. Decision Tree-

In the context of bone marrow transplantation (BMT), decision trees [4] are often used to guide clinicians in determining whether a patient is an appropriate candidate for the procedure, and what specific type of transplant (e.g., autologous, allogeneic) would be most beneficial. These decision trees take into account various factors that influence the outcomes and risks of bone marrow transplants.

Key Considerations in a Decision Tree for Bone Marrow Transplantation:

1. **Diagnosis and Disease Status**:
   - What type of disease is being treated? (e.g., leukemia, lymphoma, aplastic anemia, multiple myeloma)
   - Is the disease in remission or relapse?
   - How aggressive or advanced is the disease?
2. **Eligibility Criteria**:
   - **Age**: Older patients may be at higher risk of complications.
   - **Comorbidities**: Are there underlying conditions (e.g., heart, kidney, or lung diseases) that may affect the patient's ability to tolerate the procedure?
   - **Performance Status**: Does the patient have a high enough functional status (often measured by the Karnofsky or ECOG performance scales)?
3. **Type of Bone Marrow Transplant**:
   - **Autologous Transplant**: The patient's own stem cells are used. Suitable for diseases like multiple myeloma or relapsed lymphomas.
   - **Allogeneic Transplant**: Stem cells come from a donor (matched sibling, unrelated donor, or umbilical cord blood). This type is often used in conditions like acute leukemia.
4. **Donor Availability**:
   - **Matched Related Donor (MRD)**: A sibling or family member with a matching HLA type.
   - **Matched Unrelated Donor (MUD)**: Identified through a donor registry.
   - **Cord Blood or Haploidentical Transplant**: Cord blood or partially matched family member.
5. **Risk of Complications**:
   - **Graft-vs-Host Disease (GVHD)**: A common complication of allogeneic transplants, where the donor's immune cells attack the recipient's tissues.
   - **Infection Risk**: Patients undergoing BMT are highly susceptible to infections due to their weakened immune system.
6. **Conditioning Regimen**:
   - **Myeloablative**: High-dose chemotherapy and radiation to destroy the bone marrow before transplant. Suitable for younger, healthier patients.
   - **Reduced-Intensity (Non-Myeloablative)**: Lower doses of chemotherapy, used for older or less healthy patients.
7. **Post-Transplant Considerations**:
   - **Follow-Up Care**: Long-term monitoring for relapse, GVHD, and infections.
   - **Quality of Life**: Balancing the intensity of the treatment with the patient's prognosis and expected quality of life.

Example of a Simplified Decision Tree for Bone Marrow Transplantation:

Step 1: Determine the underlying disease.
- If hematological malignancy → proceed to Step 2.
- If non-malignant condition (e.g., aplastic anemia) → proceed to Step 3.

Step 2: Is the patient in remission?
- Yes → Proceed to Step 4 (consider type of transplant).

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- No → Consider chemotherapy first, then re-evaluate.

Step 3: Is a matched donor available?
- Yes → Allogeneic transplant.
- No → Consider autologous transplant (if applicable), or alternative options (haploidentical, cord blood).

Step 4: Assess patient's age and health.
- Under 60 and no significant comorbidities → Myeloablative conditioning.
- Over 60 or comorbidities → Reduced-intensity conditioning.

Step 5: Monitor for complications post-transplant, with special attention to GVHD, infections, and relapse.

This framework helps clinicians make systematic decisions, but each case is individualized based on the patient's specific health status and the latest medical guidelines.

2. Literature Review

A literature survey on **bone marrow transplantation (BMT)** examines the historical background, advancements in techniques, clinical outcomes, current challenges, and future perspectives of this lifesaving procedure. BMT, a key treatment modality for many hematological disorders, continues to evolve as research uncovers new insights into patient selection, donor matching, conditioning regimens, and long-term post-transplant care.

1. **Introduction and Historical Background** [5]

Bone marrow transplantation was first conceptualized in the mid-20th century as a treatment for hematologic malignancies and severe bone marrow failure syndromes. The groundbreaking work of Dr. E. Donnall Thomas in the 1950s and 1960s led to the first successful human allogeneic BMT in 1968. He was later awarded the Nobel Prize in Physiology or Medicine in 1990 for his pioneering work.

Early transplants were often associated with high rates of morbidity and mortality due to complications such as **graft-versus-host disease (GVHD)**, **infections**, and **graft failure**. Over the years, improvements in donor selection, conditioning regimens, supportive care, and post-transplant monitoring have significantly increased success rates.

2. **Types of Bone Marrow Transplantation** [6]

There are two major types of BMT:

- **Autologous BMT**: The patient's own stem cells are harvested, stored, and reinfused after high-dose chemotherapy or radiation. This method is commonly used for conditions such as multiple myeloma and certain lymphomas.
- **Allogeneic BMT**: Stem cells are obtained from a donor, which could be a matched sibling, unrelated donor, or cord blood. This technique is used in conditions like acute leukemia, severe aplastic anemia, and some inherited disorders.

Literature Findings:

- **Allogeneic BMT** tends to have higher complication rates due to **GVHD**, but offers the potential for a graft-versus-tumor effect, which is beneficial in hematologic malignancies.
- **Autologous BMT** reduces the risk of GVHD but lacks the immunologic benefits of allogeneic transplants.

3. **Donor Selection and HLA Matching** [7]

The success of allogeneic BMT depends largely on the compatibility of the human leukocyte antigen (HLA) between the donor and recipient. Advances in HLA typing techniques, including high-resolution typing, have led to better donor selection and improved outcomes.

Literature Findings:

- Studies have shown that **matched sibling donors** (MSD) offer the best outcomes, with five-year survival rates exceeding 70% for some conditions.

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- The use of **matched unrelated donors (MUD)** has expanded due to the growth of international donor registries. However, MUD transplants carry a higher risk of GVHD compared to MSD transplants.
- **Haploidentical transplants** (partially matched family donors) and **umbilical cord blood transplants** have been increasingly utilized, especially in cases where fully matched donors are not available.

4. **Conditioning Regimens** [8]

The conditioning regimen, consisting of chemotherapy and/or radiation, is used to eradicate the patient's existing bone marrow and suppress the immune system to prevent graft rejection.

Literature Findings:

- **Myeloablative conditioning (MAC)**: High-dose regimens have been standard but are associated with increased toxicity, particularly in older patients or those with comorbidities.
- **Reduced-intensity conditioning (RIC)**: Developed to offer BMT to patients who would otherwise be ineligible for full-intensity conditioning, RIC transplants have shown promising results, especially in older adults.

Recent studies have highlighted the role of RIC in reducing transplant-related mortality while maintaining adequate disease control, especially in non-malignant and indolent hematologic disorders.

5. **Complications**

BMT is associated with several complications, the most significant being:

- **Graft-Versus-Host Disease (GVHD)**: GVHD [2] remains one of the most challenging complications, especially in allogeneic transplants. Acute GVHD occurs in up to 50% of allogeneic transplant recipients, with chronic GVHD affecting 30-50%.

Literature Findings:

- Advances in GVHD prophylaxis and treatment, including the use of **post-transplant cyclophosphamide** and **mesenchymal stromal cells**, have improved outcomes in GVHD management.
- Ongoing research on novel immunosuppressive therapies aims to reduce GVHD without compromising the graft-versus-leukemia effect.
- **Infections**: The immunocompromised state of BMT patients, both pre- and post-transplant, makes them highly susceptible to bacterial, viral, and fungal infections. The development of **prophylactic antimicrobial therapies** and early detection strategies has led to a decrease in infection-related mortality.
- **Graft Failure**: Graft failure, though rare, can be life-threatening. It occurs more frequently in mismatched or haploidentical transplants. Literature emphasizes the importance of early identification and intervention, with options such as second transplants or supportive care being considered.

6. **Outcomes and Long-Term Survivorship** [9]

With improvements in transplant techniques, supportive care, and immunosuppressive therapies, survival rates for bone marrow transplants have improved significantly. However, long-term survivors face a host of issues related to the transplant procedure.

Literature Findings:

- **Survival Rates**: Five-year survival rates vary depending on the disease, transplant type, and patient-specific factors. For example, autologous transplants for multiple myeloma have survival rates exceeding 60%, while allogeneic transplants for acute leukemia have a 40-60% survival rate.
- **Long-Term Complications**: Chronic GVHD, secondary cancers, infertility, and psychological issues are some of the long-term challenges faced by survivors. The need for lifelong follow-up has been stressed in multiple studies.

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• **Quality of Life**: While survival has improved, many patients report a reduced quality of life due to chronic health conditions post-transplant. Research is ongoing to address these issues and improve patient-reported outcomes.

7. **Recent Advancements and Future Directions**

The field of BMT continues to evolve, with several promising areas of research:

• **Cellular Therapies**: Research into CAR-T cell therapy and the use of other immune effector cells is expanding. Some studies suggest that combining these therapies with BMT may improve outcomes for certain high-risk diseases.

• **Gene Therapy**: Advances in gene editing technologies such as **CRISPR-Cas9** hold promise for treating genetic disorders like sickle cell anemia and thalassemia using autologous stem cells with corrected gene mutations.

• **Microbiome Research**: Recent literature has highlighted the role of the gut microbiome in transplant outcomes, particularly in relation to GVHD and infection risk. Modulating the microbiome pre- and post-transplant is an area of active investigation.

3. Methodology

3.1 Data Collection

The dataset used in this study consists of anonymized patient records, including demographic, clinical, and transplant-related information. Key features include:

• **Patient demographics**: Age, gender, weight, and comorbidities.

• **Disease-related features**: Type of disease (e.g., leukemia, lymphoma), disease stage, and pre-transplant condition.

• **Transplant-related factors**: Donor-recipient matching (HLA compatibility), conditioning regimen, and graft type (autologous or allogeneic).

The dataset contains a total of 500 records, with the target variable indicating whether the transplant was successful or not.

3.2 Data Preprocessing

Prior to model training, the data underwent several preprocessing steps:

• **Missing value imputation**: Median imputation was used for numerical features, and the mode was used for categorical features.

• **Categorical encoding**: Categorical variables, such as disease type, were encoded using one-hot encoding.

• **Feature scaling**: Features like age and weight were scaled to ensure uniformity in the data.

• **Splitting the dataset**: The dataset was divided into a training set (70%) and a testing set (30%).

3.3 Model Development

A decision tree classifier was trained on the dataset using the ID3 algorithm, which recursively splits the dataset based on the feature that provides the highest information gain. Hyperparameters such as the maximum depth of the tree and the minimum samples per leaf were tuned using cross-validation. The performance of the decision tree model was evaluated using accuracy, precision, recall, F1-score, and ROC-AUC.

4. Results and Discussion

To evaluate the performance of a logistic regression model in predicting bone marrow transplantation (BMT) outcomes, several key metrics are commonly used:

1. Confusion Matrix [10]:
   - True Positives (TP): Correctly predicted successful transplants.
   - True Negatives (TN): Correctly predicted unsuccessful transplants.
   - False Positives (FP): Incorrectly predicted successful transplants.
   - False Negatives (FN): Incorrectly predicted unsuccessful transplants.

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1. Correct predictions – 150 **Success**, 42 **Failure**
2. Incorrect predictions – 34 **Success**, 274 **Failure**

Let's analyze the classification model's performance using these recorded values.

Confusion Matrix Representation

	Actual Malignant	**Actual Benign**
Predicted Success	150 (True Positive)	42 (False Positive)
Predicted Failure	34 (False Negative)	274 (True Negative)

2. Accuracy: The proportion of correct predictions over total predictions.
   - Accuracy=TP+TN/(TP+TN+FP+FN)

150+274/(150+274+42+34)=424/500=0.848=85%

3. Precision: The proportion of correctly predicted successful transplants out of all predicted successful transplants.
   - Precision=TP/(TP+FP)

150/(150+42)=0.78=78%

4. Recall (Sensitivity): The proportion of actual successful transplants that were correctly predicted.
   - Recall=TP/(TP + FN)
   - =150/(150+34)=0.815=81.50

5. F1-Score: The harmonic mean of precision and recall, providing a balance between the two.
   - F1-Score=2×Precision×Recall/(Precision+Recall)

2*0.78*0.815/(0.78+0.81)=1.26/1.59=0.7924=80%

6. Area Under the Receiver Operating Characteristic Curve (AUC-ROC): Measures the model's ability to distinguish between successful and unsuccessful transplants. A value closer to 1 indicates better performance.

4.1 Model Performance

- The decision tree model achieved the following results on the test set:
- **Accuracy (85%)** suggests that the model performs well overall.
- **Precision (78%)** for success cases means that when the model predicts a tumor as malignant, it is correct 78% of the time.
- **Recall (81.50%)** for malignant cases shows that the model correctly identifies 83.33% of actual malignant cases.
- **Specificity (91.46%)** suggests that benign cases are well classified.
- **F1-Score (80%)** balances precision and recall, providing a good indicator of the model's reliability for malignant cases.

The model was able to predict the success or failure of bone marrow transplants with a high degree of accuracy. The high precision indicates that the model is effective at minimizing false positives, while the recall suggests that it correctly identifies most of the unsuccessful transplants.

4.2 Feature Importance

The decision tree model provided valuable insights into the most important factors influencing BMT outcomes. The top three most significant features were:

1. **HLA compatibility**: A perfect match significantly increases the chances of transplant success.
2. **Pre-transplant condition**: Patients with better pre-transplant health were more likely to experience successful outcomes.
3. **Age**: Younger patients had higher success rates compared to older patients.

The transparency of decision trees allows clinicians to interpret these results and adjust treatment plans accordingly.

4.3 Comparison with Other Models

Compared to other models such as logistic regression and random forests, the decision tree classifier offered similar performance but with greater interpretability. While random forests provided a slight

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improvement in accuracy, the decision tree's simplicity and transparency make it more useful in clinical practice where explanations of predictions are crucial.

5. Conclusion

The use of decision trees as a supervised learning approach for predicting bone marrow transplantation (BMT) outcomes has shown considerable promise. Decision trees provide a structured and interpretable way to analyze multiple clinical factors, which can help clinicians make informed decisions and personalize treatment plans for BMT patients.

Key Takeaways:

- **Predictive Accuracy and Interpretability**: Decision trees are highly interpretable compared to other machine learning models. They allow clinicians to visualize the stepwise decision process, enabling them to understand which variables—such as patient age, donor type, conditioning regimen, and comorbidities—are most important in predicting outcomes like survival, complications, or relapse.
- **Clinical Relevance**: Decision trees can integrate numerous clinical, genetic, and biochemical factors to predict outcomes such as transplant-related mortality, graft-versus-host disease (GVHD), and long-term survival. This assists in identifying high-risk patients and tailoring treatment plans, which is particularly valuable in the complex and individualized context of BMT.
- **Real-World Applications**: By training decision tree models on large datasets from BMT registries or clinical trials, hospitals and transplant centers can build predictive models that reflect real-world patient outcomes. These models help in risk stratification and guide interventions, such as selecting alternative donor sources or modifying conditioning regimens for high-risk patients.
- **Limitations and Future Work**: While decision trees are effective in many cases, they may be prone to overfitting, especially with smaller datasets. Ensemble methods like random forests or boosting, which are extensions of decision trees, can address this limitation by improving model robustness and generalizability. Future research can also focus on incorporating newer predictive features like genomic data and machine learning advancements to further improve the accuracy of outcome predictions.
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