CHAPTER 5

EVALUATION OF CRITICAL CHARACTERISTICS IN PHARMACEUTICAL SUPPLY CHAIN MANAGEMENT USING FUZZY ANALYTIC HIERARCHY PROCESS AND IMPLEMENTING BLOCKCHAIN TECHNOLOGY TO MAINTAIN TRANSPARENCY

5.1 INTRODUCTION

One of the biggest challenges faced by the healthcare supply chain is to deliver the medicines effectively to the end users. A big risk and huge complexity are involved in the supply chain of drugs. There are numerous issues with the traditional medical supply chain, including a shortage of transparency, trouble tracking items, less confidence, and the delivery of out-of-date products. The major issue is counterfeit drugs, which is a challenge to the healthcare sector. These low-quality drugs result in the death of many innocent people who become victims of these drugs. It is the basic right of every individual to get proper healthcare services. There are a variety of drugs in the market as the disease is increasing day by day. These drugs assist the patient in temporarily reducing excruciating pain. Because the legitimacy of these manufacturer organisations is uncertain and they do not adhere to the established criteria, there are many drawbacks from these pharmaceuticals as opposed to benefits. Due to the use of these phoney pharmaceuticals, many deaths have been reported from underdeveloped nations, and children represent the majority of these victims. These medications may not aid in the patients' recovery from the illness but do have numerous harmful side effects. These medications pose a major risk to people's health. It is challenging to identify these counterfeit pharmaceuticals because they are distributed through several intricate networks. The use of the most recent advancements to keep an eye on the movement of the drug at each point of the drug supply chain is one expert suggestion for resolving and preventing the proliferation of counterfeit drugs. Other suggestions include improving management and control of the medical supplies at the pharmacy, distributor, and health centre levels. The effective management of the drug delivery supply chain is crucial to averting this problem, as shown by the considerations. The one technology that can trace and record the supply of drugs at every stage, starting with supplier raw materials, manufacturing output, distribution stage, pharmacies, health-centres and patients, respectively, is required to address this issue and prevent the sale of counterfeit medications. Additionally, Block chain is the most recent development in managing the supply chain and monitoring the goods. Block chain technology can effectively safeguard the delivery process and monitor it [Haleem et al. 2021].

The characteristics of blockchain technology, especially the way it promotes decentralisation, transparency, trust, anonymity, and stability, its usage in the pharmaceutical business has been highlighted as a practical method to thwart the distribution of fake medicines. Pharmaceuticals may be tracked using blockchains to determine where they were made, how they were transported, and where they were purchased. In the pharmaceutical industry, blockchain technology also cuts down on the number of middlemen, which lowers prices and increases safety. Blockchain Technology is intended specifically to house the history of activities for the well-known cryptocurrency referred to as Bitcoin. A comprehensive digital ledger software is offered by the blockchain to store data records and perform transaction logs in a format of organised groups of blocks. Blockchain technology is one of the secured databases, to put it more precisely. Each transaction's digital details, including the time, date, price, and parties engaged in the transaction, are recorded in a block. If we explore inside the blockchain, we find that there are numerous independent nodes that cooperate to approve transactions without knowing one another and without any form of mutual trust, the recorded data is disseminated. Every block in the blockchain contains two hash codes, called the preceding and current hash codes. The current hash code pertains to the block itself, while the previous hash code belongs for the block before it. Additionally, if one block's information changes, all of that block's information should also be updated. The network's blocks are all closely connected to one another and secured with cryptographic and transactional codes. Strong mathematical methods are another crucial component since they enable nodes that mine bitcoins to approve nodes without having their data affected, and following approval, blocks can be uploaded to the blockchain network. Because of this, the blockchain technology guarantees both security and transparency [Gad et al. 2022].

The definition of blockchain is an expanding chain of several blocks that stores data in accordance with predetermined rules. The minor blocks in the blockchain network keep on adding to create transactions. These nodes perform independently and are all controlled by the same protocol. The blockchain platform is a network of nodes that records all transactional data, data about participants, along with history. The three types of blockchain networks—private, public, and consortium—are differentiated based on their functionalities. No admin node monitors the permission-less or public blockchain networks, and regulates transactions; these transactions are monitored by the miner nodes of the blockchain. In the joint blockchain network, the admin node is the one central body responsible for managing the data and transactions. Using both public and private access, the administrator can manage the data. Depending on business terms, some of the data may be made public while other data may only be disclosed to a particular class of private players. These networks, that handle both private and public data, are not entirely decentralised. such as the Hyper Ledger Fabrics Platform. All information and transactions saved in the encrypted blockchain network are wholly private. Only the network's authorised members have access to all the details and data [Marikyan 2022].

The pharmaceutical medicine supply chain can be managed and protected best with blockchain technology. Due to its many advantages, some pharmaceutical businesses are concentrating on blockchain, while others are employing it in their supply networks. The benefit of using Blockchain Technology is that it offers a distributed decentralised ledger. This ledger can be accessed electronically by all pair nodes in the network. It allows everyone to see and authorize transaction-related data thereby making it appealing to majority sectors to use it [Habib et al. 2022]. The special feature of blockchain technology is its consensus approach that helps in avoiding duplicate transactions as well as it records only that information which is authorized in the repository. Also, this is to keep in notice that as the nodes are more in number, the likelihood of failure threshold are operational and because tolerance in fault is quite robust, the probability of a network failure is also very low.

In this research work, we have used Blockchain Technology that uses Hyper ledger fabric to control the drug delivery supply chain network. Using Blockchain Technology, we can track and monitor the delivery of drugs continuously which can help in addressing the counterfeiting of drugs. The major objective of any drug distribution supply chain is to deliver quality medicine on a promising time horizon.

In order to achieve this, we developed a machine learning-based recommendation system that is trained using a database of previously gathered medicine user reviews. This database was gathered using web crawling and contains comments and ratings depending on the disease severity of the customers. Following is a brief explanation of how our suggested system works: In order to store and share knowledge via the blockchain network efficiently and securely, a blockchain-based novel drug supply chain platform is first developed, in which the suppliers, manufacturers, distributors, pharmacies, hospitals, and clinics of the drugs delivered by the smart pharmaceutical structure serve as attendees. By connecting the apps with blockchain networks this can aid in effective utilization of Hyperledger Composer REST API. To store the transaction of medicine delivered to the end users, MongoDB is used and this is the greatest solution to the data redundancy issue and the only one that offers independent memory for each node in the blockchain network is this one. The finished product allows customers, such as patients, to authentically trace the origin of their medications. Another benefit of our system is that it uses machine learning algorithms to suggest the best and highest-rated medications to users. Additionally, the blockchain network and machine learning module are combined, allowing system users to combine both aspects of the suggested system. The models may then include the feedback and ratings from the client web application into their learning process, updating the suggested results as necessary.

The rest of the section is organized as literature review followed by overview and working of blockchain-based delivery of drugs. The prioritization method used to evaluate the critical risk factors and methods to mitigate the risks using fuzzy analytical hierarchical processes (F-AHP). Further explaining the new idea of how blockchain can help in maintaining the transparency and delivery of drugs. Also, explaining the use of machine learning helping in the drug delivery. The next section explains the working and suggesting the implementation of architecture in healthcare supply chain management followed by conclusion and future scope of the same.

5.2 LITERATURE REVIEW

People know blockchain technology as cryptocurrency came into the picture. Any organisation may become safe, effective, transparent, and decentralised by using the blockchain. Blockchain applications for non-financial domains have been pursued by researchers continuously. The healthcare sector is one of the non-financial sectors that has demonstrated a greater influence on the blockchain. However, research on creating blockchain-assisted apps is still fairly young and evolving quickly. Scientists in the healthcare sector have been working hard to stay abreast of the research sides in this area. To provide a look into the cloudy blockchain technology usage field that is part of the healthcare industry's future growth trajectory, we highlight the blockchain applications that are presently being employed in that sector.

The purpose of Fernando's literature review was to identify the factors that would lead to the success of blockchain technology applications in the pharmaceutical business. The authors performed a meta-analysis of 15 research and reported data on 21 success factors. They identified the five most important to them: trust, tracking, transparency, traceability, and real-time. Notably, these five characteristics were addressed very briefly, with no mention of blockchain applications or domain-specific difficulties [Fernando et al. 2019].

The appraisal of blockchain applications to advance the pharmaceutical business was covered in another review study [Alshahrani & Alshahrani, 2021]. Data collection techniques for quantitative analysis were utilised by the authors. They discovered that healthcare professionals' attitudes, a lack of partnership, and economic disparity were the primary barriers to blockchain adoption in Saudi Arabia's pharmaceutical business. The authors also noted a number of elements that may support blockchain applications, such as system stability, data security, enhanced supply chain management, decentralisation, interoperability, and governmental regulations. Again, Alshahrani & Alshahrani (2021) notably avoided talking about blockchain-related problems and concerns [Alamari et al. 2021].

The designs and difficulties of utilising blockchain for pharmaceutical traceability were covered by the writers in Uddin. They discussed problems with traceability of goods in the pharmaceutical supply chain and emphasised ways to use blockchain technology effectively for monitoring and tracing to reduce the use of fake medicines. The blockchain technology and the problems and difficulties associated with other sectors of the technology's uses in the pharmaceutical business were not discussed by the authors outside of the pharmaceutical supply chain [Uddin et al. 2021]. Alkurdi and colleagues have represented a systematic literature review categorizing different papers, topics, etc., explaining each category with their advantages and limitations. In the paper most of the papers are focussed on pharmaceutical supply chain giving insights of the qualitative work done so far [Alkurdi and Bustelo 2022]. Khizar Abbas in their paper has explained the use of blockchain technology in combination with machine learning for managing the pharmaceutical supply chain. They have prepared an architecture to supply drugs and another algorithm helping to choose medicines alternatives [Abbas et al. 2020]. Throughout, transaction response time, and latency were some of the key metrics used in several studies to measure the effectiveness of our system. The system's simulation findings demonstrate excellent results. This approach aids pharmaceutical firms in eradicating the issue of fake medications while also significantly boosting sales.

There are few authors who have described the use of electronic medical records helping in the medical supply chain using the help of blockchain networks. The purpose of the blockchain-based software is to safeguard each patient's proxy rights, including the right to know who else has access to their medical records. In order to share the data for upcoming research purposes, patients can share these permissions on the blockchain.

Even though the blockchain network maintains a record of every location and data exchange. Accompanying software is also required if you wish to accomplish genuine interactivity. There are few other researches where the architecture of blockchain networks is designed to provide real time information to monitor the distributed drugs in the healthcare industry. Previous research also includes technologies like RFID, electronic codes, etc., are used to track the information and record.

Hassan and colleagues have used ETHEREUM based blockchain technology to keep a track of the pharmaceutical products shipped, while in the other have included data of different enterprises. All above research has focussed on the authenticity, security, privacy and traceability of the data [8]. Though this literature review has covered major research done previously, still there is scope representing more literature. Hence, we see that blockchain technology is not just limited to cryptocurrency but there is vast scope in fields like healthcare, finance, in fact in every field. There is research happening in the field like vehicles, cloud computing, smart grid, etc.

As we can see, it is critical to quantify the risk associated with the various aspects of blockchain in the pharmaceutical supply chain. This can help in removing the counterfeiting of drugs and provide quality drugs to the customers. The F-AHP method is used to find out the relatively important characteristics of blockchain in the pharmaceutical supply chain.

5.3 METHOD USED FOR MULTI CRITERIA DECISION MAKING - FAHP

Fuzzy Analytic Hierarchy Process (FAHP) is an Analytic Hierarchy Process (AHP) method based on fuzzy logic theory. The Fuzzy AHP method is utilised in the same way that the AHP method is. It's rather that the Fuzzy AHP approach converts the AHP scale into a fuzzy triangle score that can be accessed in order of priority [Coffey and Claudio 2021].

Using this method, we calculate the weight of the different factors that are associated with the blockchain. This study uses the fuzzy approach to describe in detail the ambiguity we face in decision making of the characteristics. It helps us to understand each characteristic by using cultural variables that are further demonstrated in triangular form as fuzzy integers. Figure 5.1 depicts the membership function of the triangular fuzzy number [Murshid and Ahmed 2011].

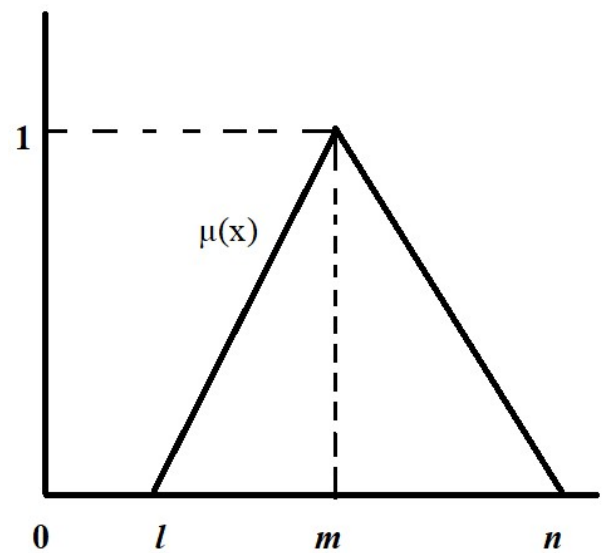

Figure 5.1 Membership Function showing triangular fuzzy number

The centre of area defuzzification method was utilised in this work to turn the fuzzy assessments into the associated crisp values. The following are the primary stages in the technique used in this study:

Step 1: First step is used to define the problem for decision making. In our case, the decision making is to prioritize the characteristics that blockchain has on the pharmaceutical supply chain.

Step 2: In the next step the complex problem is then decomposed in a hierarchical framework containing decision elements. In our study, we have used two hierarchical stages.

Step 3: Here, we create a pairwise comparison matrix of the parameters using triangular fuzzy numbers and estimate their weight. As shown in Table 5.1, a nine-point scale was used to quantify the relative relevance of goal-related factors. A geometric mean approach was used to calculate the fuzzy weights of the criteria.

Table 5.1 Satty's Crisp scale and fuzzified scale used for pairwise comparison

Satty's Crisp Scale		**Judgement definition**	**Triangular fuzzy scale**	**Triangular fuzzy inverse scale**
1	NI	Not at all Important	(1, 1, 3)	(0.33, 1, 1)
2	SI	Slightly Important	(1, 3, 5)	(0.2, 0.33, 1)
3	VI	Very Important	(3, 5, 7)	(0.143, 0.2, 0.33)
4	FI	Fairly Important	(5, 7, 9)	(0.11, 0.143, 0.2)
5	HI	Highly Important	(7, 9, 9)	(0.11, 0.11, 0.143)

Further, a google form was circulated among the expertise people related to healthcare to get the pairwise comparison. The experts were asked to fill the data based on their experience, thus, ensuring participation of the different people such as medical practitioners, medical representatives, research, experts, etc. By summing the data and removing the errors and biases from the data, a decision was made as presented in Table 5.3. The details of the characteristics taken into consideration are presented in Table 5.2.

Table 5.2 Characteristics of pharmaceutical supply chain for pairwise comparison

Sr. No.	Characteristics	Represented by
1	Transparency	C1
2	Traceability	C2
3	Data Integrity	C3
4	Security	C4
5	Supplier Verification	C5
6	Manufacturer Verification	C6
7	Product Authentication	C7
8	Compliance and Regulatory Requirements	C8
9	Smart Contract Integration	C9
10	Interoperability	C10
11	Integration	C11
12	Risk Assessment	C12
13	Cost Analysis	C13
14	Efficiency Analysis	C14
15	Data Privacy	C15
16	Consent Management	C16
17	Sustainability and Environmental Impact	C17
18	Scalability	C18
19	Performance	C19

The table presents a structured overview of several aspects linked with the use of blockchain technology in supply chain management. Each characteristic is given a unique identification, which is represented by a corresponding abbreviation (for example, transparency is denoted by C1). Transparency, traceability, data integrity, security, supplier verification, manufacturer verification, product authentication, regulatory compliance, smart contract integration, interoperability, integration, risk assessment, cost analysis, efficiency analysis, data privacy, consent management, sustainability and environmental impact, scalability, and performance are all listed in the Table 5.3.

Table 5.3 Pairwise comparison matrix of characteristics of pharmaceutical supply chain

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19
C1	(1,1,1)	(7,9,9)	(7,9,9)	(7,9,9)	(7,9,9)	(7,9,9)	(7,9,9)	(3,5,7)	(1,3,5)	(3,5,7)	(5,7,9)	(5,7,9)	(7,9,9)	(7,9,9)	(7,9,9)	(5,7,9)	(1,3,5)	(1,1,3)	(1,3,5)
C2	(0.11,0.11,0.143)	(1,1,1)	(5,7,9)	(3,5,7)	(7,9,9)	(7,9,9)	(7,9,9)	(1,3,5)	(1,3,5)	(5,7,9)	(5,7,9)	(1,1,3)	(1,3,5)	(3,5,7)	(7,9,9)	(1,1,3)	(1,1,3)	(1,3,5)	(1,1,3)
C3	(0.11,0.11,0.143)	(0.11,0.143,0.2)	(1,1,1)	(3,5,7)	(5,7,9)	(5,7,9)	(7,9,9)	(1,1,3)	(1,3,5)	(5,7,9)	(5,7,9)	(1,3,5)	(3,5,7)	(3,5,7)	(7,9,9)	(3,5,7)	(1,3,5)	(1,1,3)	(3,5,7)
C4	(0.11,0.11,0.143)	(0.143,0.2,0.33)	(0.143,0.2,0.33)	(1,1,1)	(5,7,9)	(5,7,9)	(5,7,9)	(1,3,5)	(3,5,7)	(3,5,7)	(5,7,9)	(5,7,9)	(1,3,5)	(1,3,5)	(7,9,9)	(1,1,3)	(1,1,3)	(1,3,5)	(3,5,7)

C5	(0.11,0.11,0.143)	(0.11,0.11,0.143)	(0.11,0.143,0.2)	(0.11,0.143,0.2)	(1,1,1)	(7,9,9)	(7,9,9)	(3,5,7)	(5,7,9)	(3,5,7)	(3,5,7)	(5,7,9)	(7,9,9)	(7,9,9)	(5,7,9)	(1,1,3)	(1,3,5)	(3,5,7)	(5,7,9)
C6	(0.11,0.11,0.143)	(0.11,0.11,0.143)	(0.11,0.143,0.2)	(0.11,0.143,0.2)	(0.11,0.11,0.143)	(1,1,1)	(7,9,9)	(7,9,9)	(5,7,9)	(1,1,3)	(1,1,3)	(3,5,7)	(7,9,9)	(7,9,9)	(5,7,9)	(1,1,3)	(1,3,5)	(3,5,7)	(5,7,9)
C7	(0.11,0.11,0.143)	(0.11,0.11,0.143)	(0.11,0.11,0.143)	(0.11,0.143,0.2)	(0.11,0.11,0.143)	(0.11,0.11,0.143)	(1,1,1)	(7,9,9)	(3,5,7)	(3,5,7)	(3,5,7)	(5,7,9)	(5,7,9)	(3,5,7)	(5,7,9)	(1,3,5)	(1,3,5)	(3,5,7)	(7,9,9)
C8	(0.143,0.2,0.33)	(0.2,0.33,1)	(0.33,1,1)	(0.2,0.33,1)	(0.143,0.2,0.33)	(0.11,0.11,0.143)	(0.11,0.11,0.143)	(1,1,1)	(1,1,3)	(1,1,3)	(1,1,3)	(1,1,3)	(3,5,7)	(3,5,7)	(3,5,7)	(7,9,9)	(7,9,9)	(1,3,5)	(1,3,5)
C9	(0.2,0.33,1)	(0.2,0.33,1)	(0.2,0.33,1)	(0.143,0.2,0.33)	(0.11,0.143,0.2)	(0.11,0.143,0.2)	(0.143,0.2,0.33)	(0.33,1,1)	(1,1,1)	(7,9,9)	(7,9,9)	(5,7,9)	(5,7,9)	(1,1,3)	(3,5,7)	(1,1,3)	(1,1,3)	(1,3,5)	(1,1,3)

C10	(0.143,0.2,0.33)	(0.11,0.143,0.2)	(0.11,0.143,0.2)	(0.143,0.2,0.33)	(0.143,0.2,0.33)	(0.33,1,1)	(0.143,0.2,0.33)	(0.33,1,1)	(0.11,0.11,0.143)	(1,1,1)	(7,9,9)	(3,5,7)	(5,7,9)	(3,5,7)	(7,9,9)	(5,7,9)	(1,3,5)	(1,3,5)	(3,5,7)
C11	(0.11,0.143,0.2)	(0.11,0.143,0.2)	(0.11,0.143,0.2)	(0.11,0.143,0.2)	(0.143,0.2,0.33)	(0.33,1,1)	(0.143,0.2,0.33)	(0.33,1,1)	(0.11,0.11,0.143)	(0.11,0.11,0.143)	(1,1,1)	(7,9,9)	(1,1,3)	(3,5,7)	(1,3,5)	(1,1,3)	(1,1,3)	(1,3,5)	(3,5,7)
C12	(0.11,0.143,0.2)	(0.33,1,1)	(0.2,0.33,1)	(0.11,0.143,0.2)	(0.11,0.143,0.2)	(0.143,0.2,0.33)	(0.11,0.143,0.2)	(0.33,1,1)	(0.11,0.143,0.2)	(0.143,0.2,0.33)	(0.11,0.11,0.143)	(1,1,1)	(5,7,9)	(1,3,5)	(5,7,9)	(1,3,5)	(1,1,3)	(3,5,7)	(3,5,7)
C13	(0.11,0.11,0.143)	(0.2,0.33,1)	(0.143,0.2,0.33)	(0.2,0.33,1)	(0.11,0.11,0.143)	(0.11,0.11,0.143)	(0.11,0.143,0.2)	(0.143,0.2,0.33)	(0.11,0.143,0.2)	(0.11,0.143,0.2)	(0.33,1,1)	(0.11,0.143,0.2)	(1,1,1)	(7,9,9)	(3,5,7)	(1,3,5)	(1,1,3)	(5,7,9)	(3,5,7)
C14	(0.11,0.11,0.143)	(0.143,0.2,0.33)	(0.143,0.2,0.33)	(0.2,0.33,1)	(0.11,0.11,0.143)	(0.11,0.11,0.143)	(0.143,0.2,0.33)	(0.2,0.33,1)	(0.11,0.11,0.143)	(0.143,0.2,0.33)	(0.143,0.2,0.33)	(0.2,0.33,1)	(0.11,0.11,0.143)	(1,1,1)	(1,1,3)	(1,1,3)	(1,1,3)	(3,5,7)	(7,9,9)

C15	(0.11,0.11,0.143)	(0.11,0.11,0.143)	(0.11,0.11,0.143)	(0.11,0.11,0.143)	(0.11,0.143,0.2)	(0.11,0.143,0.2)	(0.11,0.143,0.2)	(0.143,0.2,0.33)	(0.11,0.11,0.143)	(0.11,0.11,0.143)	(0.2,0.33,1)	(0.11,0.143,0.2)	(0.143,0.2,0.33)	(0.33,1,1)	(1,1,1)	(7,9,9)	(3,5,7)	(3,5,7)	(1,3,5)
C16	(0.11,0.143,0.2)	(0.33,1,1)	(0.143,0.2,0.33)	(0.33,1,1)	(0.33,1,1)	(0.33,1,1)	(0.2,0.33,1)	(0.11,0.11,0.143)	(0.33,1,1)	(0.11,0.143,0.2)	(0.33,1,1)	(0.2,0.33,1)	(0.2,0.33,1)	(0.33,1,1)	(0.11,0.11,0.143)	(1,1,1)	(5,7,9)	(1,3,5)	(1,3,5)
C17	(0.2,0.33,1)	(0.33,1,1)	(0.2,0.33,1)	(0.33,1,1)	(0.2,0.33,1)	(0.2,0.33,1)	(0.2,0.33,1)	(0.11,0.11,0.143)	(0.33,1,1)	(0.2,0.33,1)	(0.33,1,1)	(0.33,1,1)	(0.33,1,1)	(0.33,1,1)	(0.143,0.2,0.33)	(0.11,0.143,0.2)	(1,1,1)	(3,5,7)	(1,3,5)
C18	(0.33,1,1)	(0.2,0.33,1)	(0.33,1,1)	(0.2,0.33,1)	(0.143,0.2,0.33)	(0.143,0.2,0.33)	(0.143,0.2,0.33)	(0.2,0.33,1)	(0.2,0.33,1)	(0.2,0.33,1)	(0.2,0.33,1)	(0.143,0.2,0.33)	(0.11,0.143,0.2)	(0.143,0.2,0.33)	(0.143,0.2,0.33)	(0.2,0.33,1)	(0.143,0.2,0.33)	(1,1,1)	(7,9,9)
C19	(0.2,0.33,1)	(0.33,1,1)	(0.143,0.2,0.33)	(0.143,0.2,0.33)	(0.11,0.143,0.2)	(0.11,0.143,0.2)	(0.11,0.11,0.143)	(0.2,0.33,1)	(0.33,1,1)	(0.143,0.2,0.33)	(0.143,0.2,0.33)	(0.143,0.2,0.33)	(0.143,0.2,0.33)	(0.11,0.11,0.143)	(0.2,0.33,1)	(0.2,0.33,1)	(0.2,0.33,1)	(0.11,0.11,0.143)	(1,1,1)

The experts chosen for getting this pairwise decision matrix is from the healthcare area, such as medical practitioners, medical representatives, academicians, researchers, etc. Professionals with diverse expertise from the healthcare sector, including medical practitioners, medical representatives, academicians, and researchers, were selected to create a pairwise decision matrix. This varied representation ensured a comprehensive perspective on blockchain's implementation in pharmaceutical supply chains. Medical practitioners provided practical insights, medical representatives contributed operational viewpoints, while academicians and researchers brought theoretical and evidence-based insights. This diverse input ensured a well-rounded and informed analysis of characteristics for effective blockchain integration in the pharmaceutical supply chain.

Step 4: Conversion of the numbers into a crisp value: Here, we take into consideration fuzzy evaluation for characteristic i as (l_i, m_i, n_i) as

l_i = lower value

m_i = middle value

n_i = higher value

To convert every characteristic value into crisp value for fuzzy evaluation, centre of area method is used as:

$$W_i = (l_i + m_i + n_i)/3 \tag{1}$$

Figure 4 represents the flow chart summarizing the AHP method used for evaluation of important characteristics of the pharmaceutical supply chain.

In the next section, a crisp weight table for the pharmaceutical supply chain is presented.

5.4 RESULTS

After getting the crisp weight of each characteristic, weight is synthesized for each characteristic with a triangular fuzzy matrix based on the characteristics that are associated with the pharmaceutical supply chain. Figure 5.1 represents the synthesized weights for ranking the best criterion having maximum success of the blockchain technology.

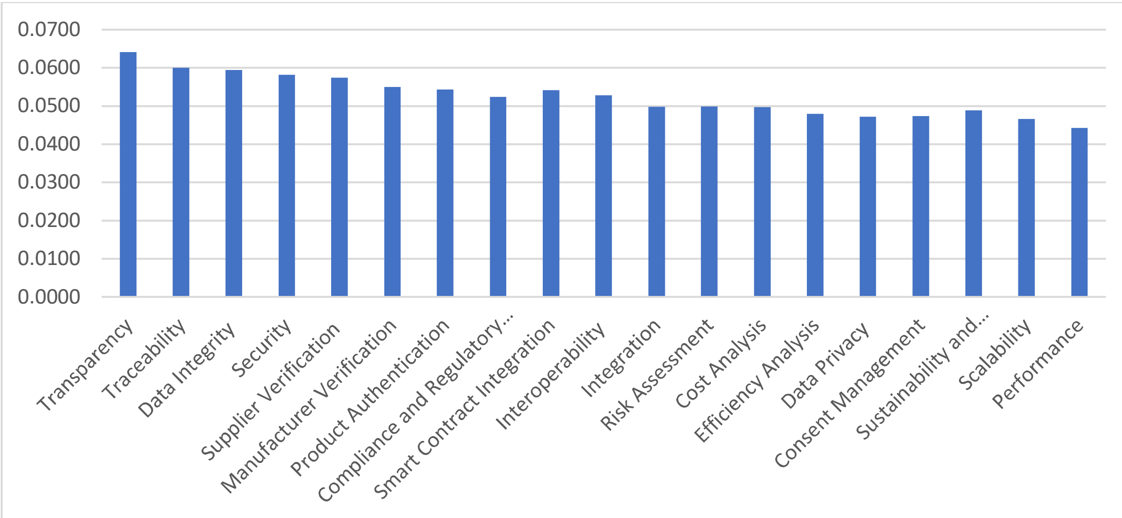

Figure 5.2 Synthesized weights for ranking of characteristic of blockchain technology that success the pharmaceutical supply chain

From the figure transparency is the most crucial characteristic in the pharmaceutical supply chain. Hence, to maintain transparency in the supply chain, blockchain technology can prove wonders to the pharmaceutical supply chain. And also, we can see from the figure, data privacy is at the most risk factor. As a result, the data in the application must be handled with extreme caution.

5.4.1 WORKING OF TRADITIONAL DRUG DISTRIBUTION SYSTEM

There is huge complexity in the existing pharmaceutical supply chain, they lack a flexible, economical, and reliable supply chain. Pharmaceutical supply chain encompasses the creation of new products, their manufacture, packaging, distribution to pharmacies, retailers, and wholesalers, as well as to patients directly. Pharmaceutical systems operate by first making the products, storing them, and thus lowers their cost-effectiveness. There are many challenges which pharmaceutical companies face such as storing at the correct temperature, transportation from one place to another, etc. The major issue is to stop the counterfeiting of the drugs which requires immediate attention [Moosivand et al. 2019].

The traditional working of drug supply chain management is shown in the figure 5.2:

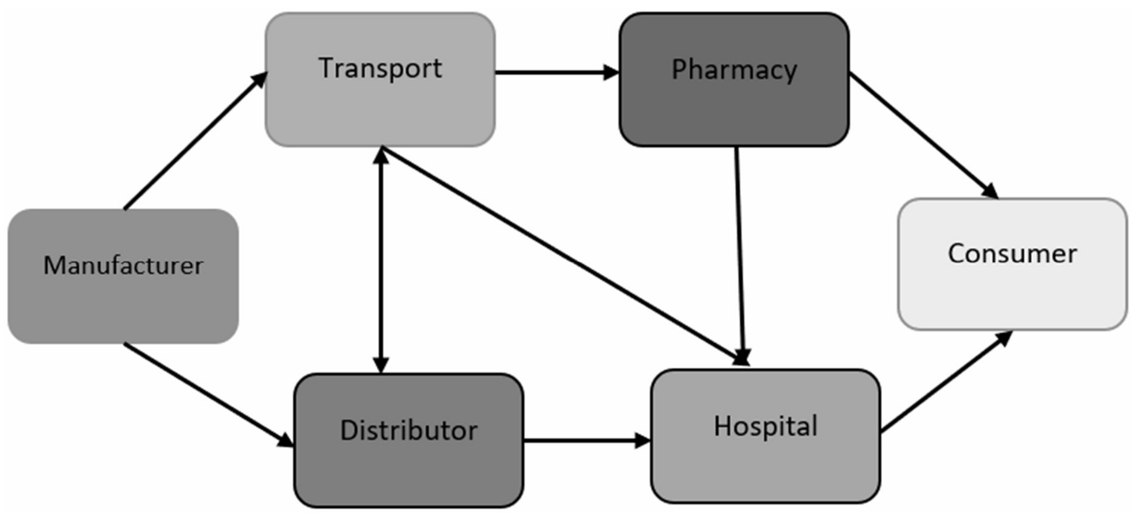

Figure 5.3 Traditional Drug Supply Chain Process [Sahoo et al. 2020]

As we see in the figure above, generally six different hoops are available in the drug delivery supply chain viz., manufacturer, distributor, transporter, pharmacy, healthcare centre, and the end user i.e., consumer (patient). Due to these numerous links within the supply of drugs from manufacturer to end consumers, the counterfeiting of drugs/medicines becomes more vulnerable. In order to incorporate transparency in the system, blockchain technology can be framed within these links. Also, the drug delivery supply chain before applying blockchain technology has many other challenges too. The material or ingredient supplied may be from an unidentified source. It may also happen that patients are unaware of the prices and may end up paying high prices. The current drug supply chain has many loopholes such as proper labelling is necessary on medical stuffs, keeping an eye on the perishable items, using same software across all the delivery stores to keep the account of the stocks, finances, etc [12].

So, the benefits of Blockchain are clear. Whenever items go through a delicate production process and where major liability and reputation problems are interwoven with the finished product, things rely on blockchain technology. As a result, another area in which Blockchain technology is being used is in the pharmaceutical industry's medication research, development, and production. But before proceeding, let's see whether it is advisable to use blockchain technology or not. For this we have used Decision Tree as shown in Figure 5.3 below:

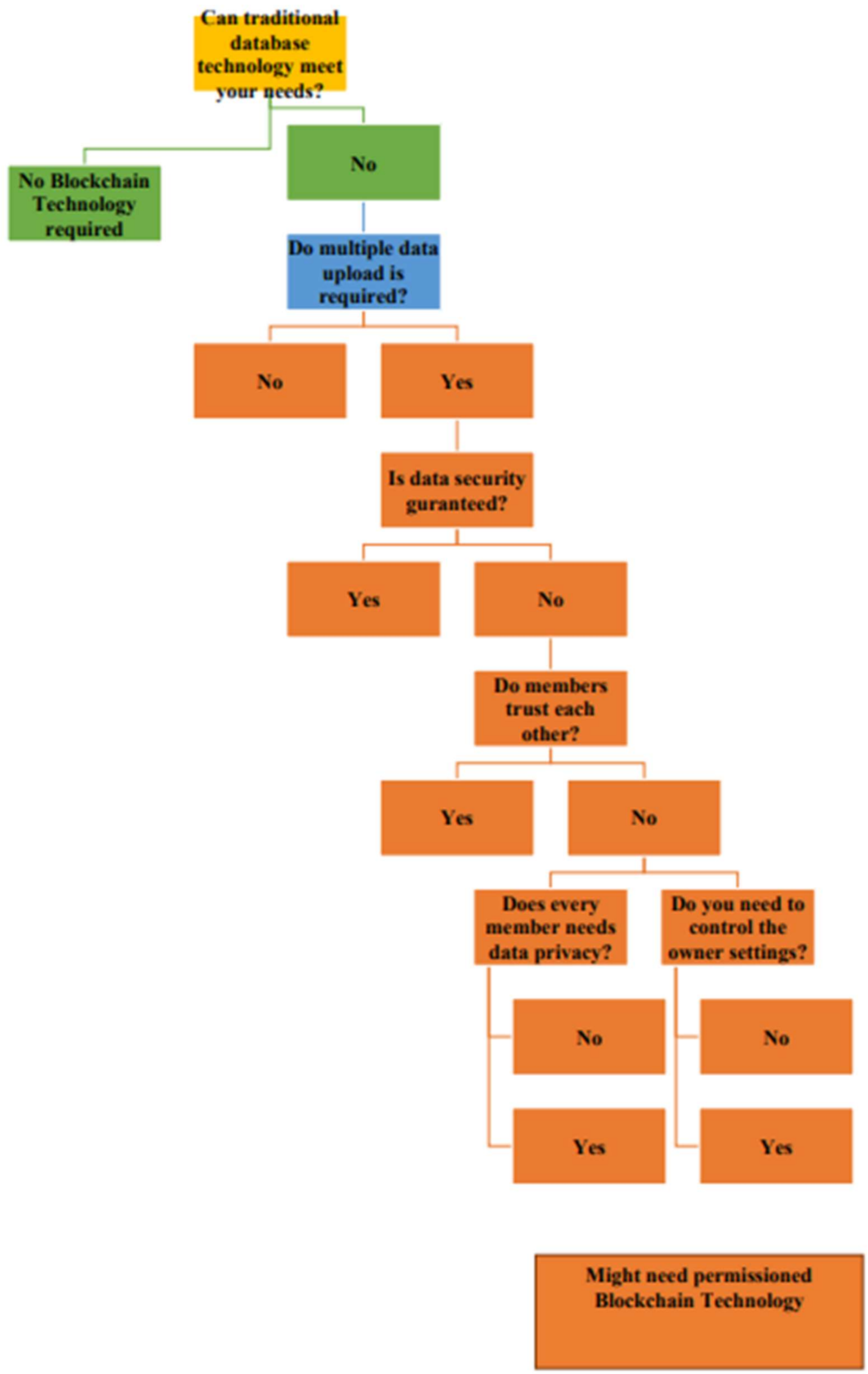

Figure 5.4 Choosing whether or not to use Blockchain Technology

According to the above decision flow chart, it is suggested that permissible blockchain is required to ensure transparency and to avoid counterfeiting of drugs in drug supply chain management. In this section we introduce the architecture of a new drug supply chain using blockchain technology. Following are the steps to record information in the blockchain architecture.

1. It is required to incorporate blockchain framework right from the first stage of the chain. A manufacturer will comply with the barcode/RFID tag on the raw material containing all the information required. It should be noted that this is the most crucial stage of the chain. It is expected to validate almost 51% correct information of the right items via supplier to all the raw materials, then the same information is recorded to the blockchain with the help of RFID/Barcode. Once the block information is validated by 51% of the members, the block is added to the chain. This ensures the visibility of the supply chain to all the members of blockchain for information regarding the quantity, quality of material, etc.

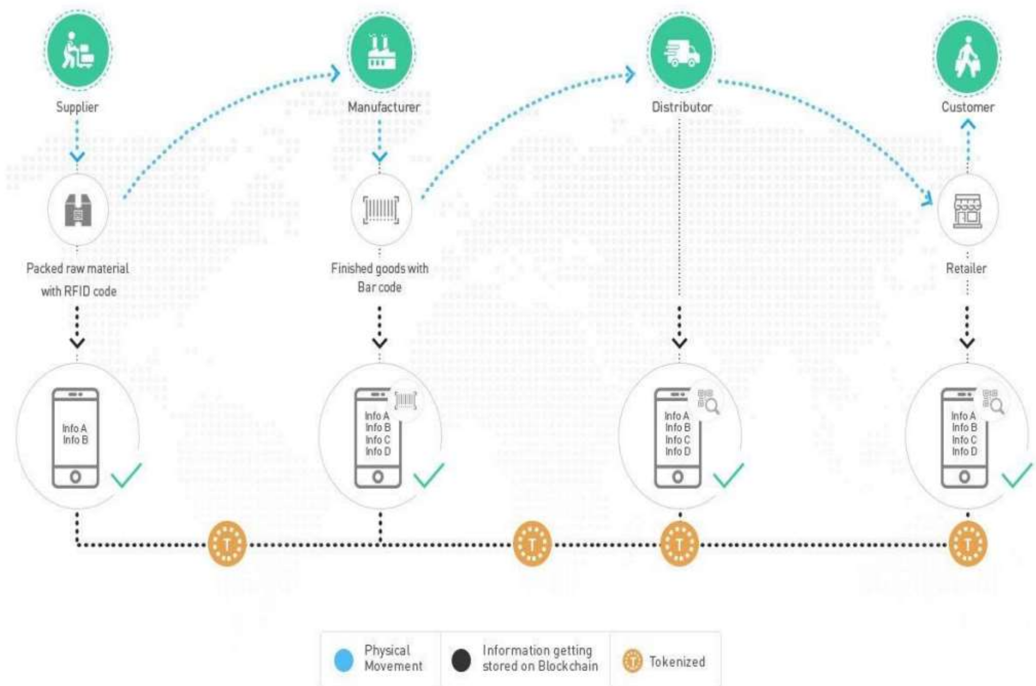

Figure 5.5 Process of storing information in Blockchain architecture.

2. After the supplier provides raw materials, the next stage manufacturing/procurement firm comes into the picture. After getting the information entered by the supplier, the manufacturer will record the information in the blockchain architecture. The same information shall be approved by more than 51% of the members to approve the entry in the blockchain.
3. The same process is to be followed for all the blocks in the chain. This includes stockists, retailers, last but not the least, patients (end-users/customers). The members will check the information of the previous chain and enter the details of their respective blocks, thereby making it available for members following the chain. This increases the pharmaceutical supply chain cost-effective and efficient.
4. The same chain will be applicable in case of reverse logistics following the reverse procedure from customer to manufacturer.

It is worth noting that we can easily avoid entering the information of the customer, as it will increase the load on the change due to the vastness of the dataset of customers. So, the chain has merely two major functions taking place in each of the transactions, viz information sent by one block and information received by the following block. To confirm that the information travels and receives both the end, a shared ledger is signed digitally. In order to make the chain secure during transportation, which is having the maximum chances of doing counterfeiting of drugs, wireless sensors and IoT can help in tracking the same information. This wireless sensor can be hidden in the package which will also help to know the other characteristics of the package such as humidity, temperature, etc., thereby helping in avoiding the spoilage of drugs. The sample of the transactions is represented in Table 5.4.

Table 5.4 Details of transactions (sample)

Sr. No.	Date	Drug Detail	Sender	Receiver	Status	Digital Sign
1	20/03/2023	Paracetamol	Manufacturer	Retailer	Verified	YgX@eG$
2	22/03/2023	Aspirin	Retailer	Customer	Verified	OjD4&y#

So, this can be used to make the system transparent. We can make digital signs different for public and private users to make it more traceable. Automating this procedure allows the framework to determine if the drug sent by the sender has previously been received by a node. In such a case, the transaction shouldn't even be started, and the rogue node may be found.

5.4.2 MANAGERIAL INSIGHTS

The examination of synthesized weights reveals that transparency is critical in the pharmaceutical supply chain, implying that blockchain has the potential to improve transparency and data protection. Traditional drug delivery suffers storage and counterfeiting issues, which blockchain can alleviate. The decision tree encourages the use of blockchain for transparency. Shared ledgers and digital signatures are included in the proposed architecture to ensure secure transactions. Wireless sensors and IoT enhance transportation security. Traceability is improved via automation and unique signatures. This method has the potential to alter the pharmaceutical supply chain, increasing efficiency and consumer trusts.

5.5 DATASET

The dataset utilized in this study has been acquired from Kaggle, a reputable online platform for datasets [Kaggle.com]. The dataset is structured in a tabular format, encompassing a comprehensive array of attributes that pertain to financial transactions within the context of healthcare.

The dataset exhibits a diverse range of information, encompassing unique identifiers (IDs), account IDs, transaction dates, transaction types, operational codes, data values, evidence details, and symbolic labels. These attributes collectively capture a multifaceted perspective of each financial transaction. For instance, the "transaction type" attribute signifies the nature of the transaction, shedding light on whether it involves a purchase, withdrawal, transfer, and so forth. In a similar vein, "operational codes" provide insights into the specific operation conducted during the transaction, while "data values," "evidence," and "symbolic labels" offer supplementary contextual details linked to each transaction entry. This dataset serves as a window into the intricate web of transactional activities within the healthcare landscape, opening doors for potential insights and predictive analyses through the application of advanced machine learning algorithms.

Table 5.5 Dataset Representation

ID	ACCOUNT ID	TYPE	OPERATION	DATA	EVIDENCE	K SYMBOL
75	0	0	20	582	2	CHAIN1
55	0	0	38	148	2.7	CHAIN2
65	0	0	20	112	0.6	CHAIN3
50	1	0	20	122	1.1	CHAIN4
65	1	1	20	60	1.3	CHAIN5
90	1	0	40	70	1	CHAIN6
75	1	0	15	582	2.3	CHAIN7
60	1	1	60	23	1.1	CHAIN8
65	0	0	65	249	1	CHAIN1
80	1	0	35	159	1.18	CHAIN2

Following is the brief explanation of the entries of the columns in the dataset.

1) Id: This column represents a unique identifier assigned to each entry in the dataset. It distinguishes individual transactions or records from one another.

2) Account id: This column signifies the account identifier associated with each transaction. It indicates the specific account involved in the transaction.

3) Type: The "Type" column categorizes the type of transaction undertaken. It could denote whether the transaction is a purchase, withdrawal, transfer, and so on.

4) Operation: The "Operation" column describes the specific operation executed during the transaction. It provides details about the action performed.

5) Data: The "Data" column holds numerical data associated with the transaction. It could represent a numerical value linked to the transaction's nature.

6) Evidence: The "Evidence" column contains evidence-related information relevant to the transaction. It could include supporting documentation or information that validates the transaction.

7) K symbol: The "K symbol" column comprises symbolic labels that characterize the transaction. Here chain refers to a certain category, label, or designation associated with the transaction.

The "Type" column within the dataset contains values ranging from 0 to 9, and each number corresponds to a specific transaction type. This column plays a pivotal role in categorizing and characterizing the nature of each financial transaction captured in the dataset. The numbers assigned to the transaction types offer a convenient and standardized way to identify and differentiate various types of transactions.

Table 5.6 Type of Transactions

NUMERIC VALUE	TRANSACTION TYPE
0	PURCHASE
1	WITHDRAWAL
2	DEPOSIT
3	TRANSFER

4	REFUND
5	BILL PAYMENT
6	DONATION
7	INTEREST EARNED
8	FEE CHARGED
9	INVESTMENT

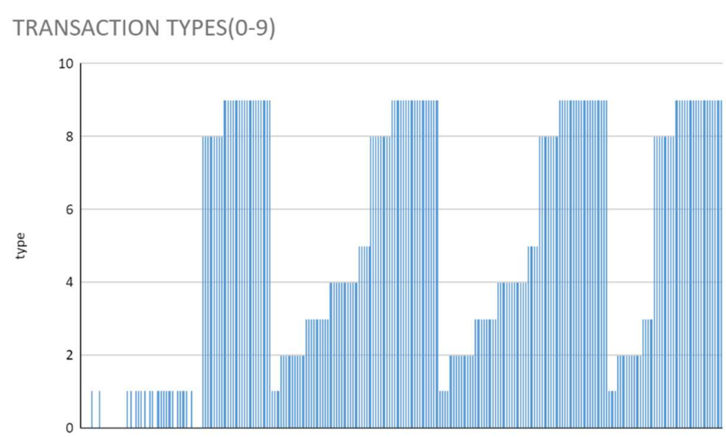

Figure 5.6 Bar chart representing transaction types

Fig 5.6 Illustrates the distribution of various transaction types that took place over a period.

5.5.1 ALGORITHMS USED

The Random Forest and Gradient Boosting algorithms have both exhibited improved accuracy in this project. These algorithms have the potential to significantly improve the precision of transaction type prediction inside the healthcare information.

The Random Forest method works by constructing a system of decision trees, each of which produces predictions, which are then combined to produce a comprehensive and precise result. By introducing randomization through feature selection and employing bootstrap sampling, it effectively prevents overfitting, an issue with complicated healthcare data characterized by multiple attributes. Notably, its ability to evaluate feature importance makes it easier to identify the critical aspects influencing transaction type prediction in a complicated healthcare context.

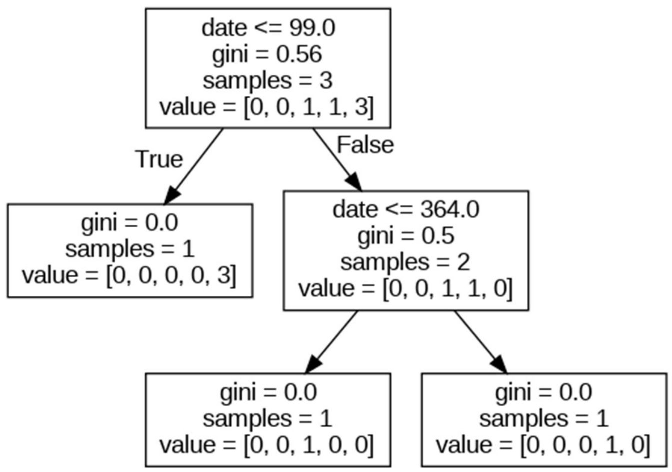

Figure 5.7 Decision Tree for Random Forest Algorithm

Fig 5.7. shows the simple Random Forest diagram, which involves a decision tree. Each node in the tree indicates a choice based on a particular aspect of the supplied data. The diagram illustrates how the decision tree makes successive decisions to classify the data samples.

1) Root Node: A root node is located at the top of the tree. It indicates the first point of decision based on a given feature. The root node here is found out by selecting a random selection of features.

2) Internal Nodes: Internal nodes, denoted by rectangles, represent intermediate decision points. These nodes analyze several properties and make judgments on how to proceed based on their values.

3) Branches: The branches that emerge from each internal node indicate the many outcomes of the feature under consideration. Based on the feature values, the data samples are steered along these branches.

4) Leaf Nodes: Leaf nodes are the end nodes of the tree. A class prediction is represented by each leaf node. Each tree in the Random Forest ensemble predicts a class individually for a given input sample, and the final prediction is chosen by majority vote among all the individual trees.

5) Split Criteria: The parameters used to determine which characteristic to examine at each node and how to split the data are designed to maximize the homogeneity of the samples within each resulting branch.

The basic equation that works behind the random forest is depicted below,

$$\hat{y} = (1/T)\sum_{i=1}^{T} \quad f(x) \tag{1}$$

In the equation, $\hat{y}$ is the predicted output for the given input of *x*. *T* represents the total number of decision trees in the Random Forest ensemble. *f(x)* prediction made by decision tree in the ensemble for input *x.*

By compiling several weak learners, the Gradient Boosting approach, on the other hand, makes use of the addition to progressively improve predictions through the optimization of gradient descent. By carefully resolving examples that were incorrectly classified, this adaptive method optimizes model working and leads to highly accurate forecasting. The algorithm is a perfect option for capturing the intricacies included in healthcare transactions since it is skilled at removing overfitting and has the ability to decipher subtle patterns hidden within the data. Its iterative learning process strengthens its predictive abilities even more, especially in situations when exact insights are crucial.

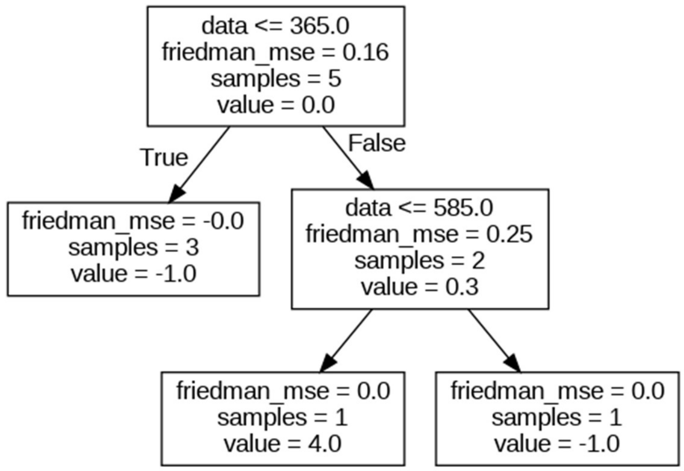

Figure 5.8 Gradient Boosting basic diagram

In Fig. 5.8, an order of decision trees is displayed, showing the process by which the Gradient Boosting method generates an ensemble model for classification.

1) Initial Prediction: At the start, there is an initial prediction, which is frequently depicted by a simple horizontal line. This prediction is frequently set to the target variable's mean value for regression or the last class for classification.

2) Residual Calculation: For each data sample, the subtraction between the actual values that belong to the target and the initial forecasts (residuals) is determined. These residuals indicate the initial model's errors and influence the design of subsequent decision trees.

3) First Decision Tree: To anticipate the estimated residuals, the first decision tree is trained. The purpose of this tree is to remedy the inaccuracies generated by the first forecast. It is made up of a subset of features and a subset of data.

4) Weighted Sum of Predictions: The first tree's predictions are multiplied by a learning rate and added to the starting predictions. As an updated prediction, this weighted sum is used.

5) Second Decision Tree: The residuals that remain after considering the initial tree's predictions are used to train the second decision tree. The goal of this tree is to rectify any lingering inaccuracies in the updated predictions.

6) Sequential Addition: Iteratively, the process of training new decision trees and updating predictions is repeated. Each new tree aims to reduce the mistakes introduced by the cumulative forecasts of all preceding trees.

7) Final Prediction: Summing the forecasts of all the separate decision trees yields the final prediction. The model's accuracy improves as a result of the cumulative effect of numerous trees working together.

8) Stopping Criterion: When a set number of trees or a specific level of improvement is reached, the algorithm stops adding new trees.

The diagram effectively illustrates the iterative nature of the Gradient Boosting algorithm, where each decision tree addresses the errors of the previous predictions and progressively improves the model's performance. The basic equation that works behind gradient boosting is shown below.

$$\hat{y} = (1/T)\sum_{i=1}^{T} \quad f(x).\gamma \qquad 2)$$

In the equation, $\hat{y}$ is the predicted output for the given input of x. T represents the total number of decision trees in the Gradient Boosting ensemble. f(x) prediction made by decision tree in the ensemble for input x. Additionally, γ is the learning rate, which scales the contribution of each decision tree's prediction to the final output.

The Random Forest and Gradient Boosting algorithms have both been useful in predicting the transaction types in healthcare data recorded on a blockchain. These algorithms have considerably improved the accuracy and reliability of transaction type predictions by using the power of machine learning, hence improving the efficiency of healthcare data administration.

Random Forest, with its ensemble of decision trees, is capable of capturing subtle patterns and relationships in data. The algorithm's randomization and built-in variance reduction techniques make it well-suited for dealing with complicated and high-dimensional datasets like those seen in healthcare. Random Forest reduces the danger of overfitting by combining the predictions of numerous trees and gives robust predictions that correlate with the different transaction types prevalent in healthcare data.

Gradient Boosting, on the other hand, takes an iterative approach to model construction, with each succeeding decision tree focusing on correcting the faults committed by the prior ones. This adaptive learning approach enables the program to adjust to data peculiarities, iteratively improving prediction accuracy. Gradient Boosting intelligently modifies the contributions of individual trees with the use of a learning rate, ensuring a balance between model complexity and generalization.

The complexity and diversity of transaction types in healthcare necessitate precise projections. Random Forest and Gradient Boosting both excel at dealing with such complexities, with complementary strengths. While Random Forest excels at capturing varied correlations, Gradient Boosting iterative nature allows it to fine-tune predictions progressively. These algorithms, when combined, lay the path for accurate transaction type predictions in healthcare data, creating a more efficient and informed healthcare ecosystem.

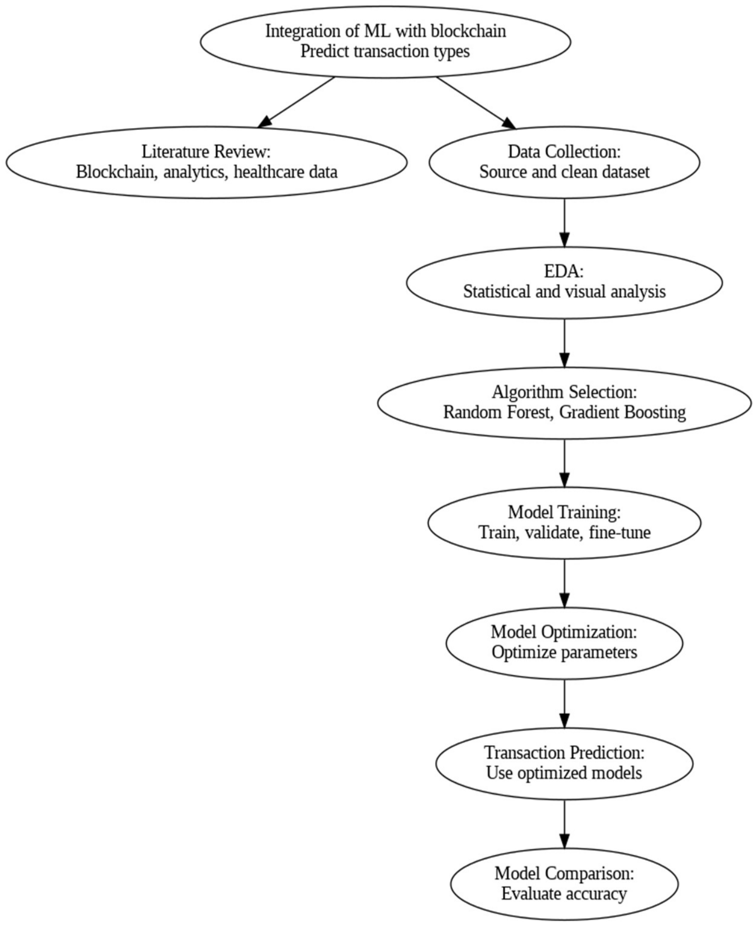

Figure 5.9 Workflow of Proposed Methodology

Fig 5.9 is the compact flowchart that illustrates the key stages of a project that focuses on integrating machine learning (ML) algorithms with blockchain technology to predict transaction types within healthcare data. The diagram conveys the project's progression through various steps and the flowchart effectively captures the sequential progression of the project's stages, from research and data preparation to advanced modeling and performance evaluation, all within a compact and easily understandable visual representation.

5.6 RESULTS

To enable the anticipation of diverse transaction classifications grounded on individual contributions, this model construct operates as an interactive mechanism. Enabling engagement from users, it facilitates the input of values pertaining to multiple columns within the dataset, with the exception of the "type" category. This procedure is designed to replicate real-life scenarios where fresh transactional data necessitates identification.

With the help of machine learning algorithms, notably Random Forest and Gradient Boosting, the system capitalizes on the insights extracted from historical dataset content. These algorithms have an understanding of the intricate relationships and patterns intrinsic to the dataset, which they use to precisely categorize transaction types. When users provide inputs such as account_id, date, operation, data, evidence, and k_symbol, the model orchestrates these inputs through the trained algorithms to produce educated forecasts regarding the probable transaction category linked with the given inputs.

```
user_input = [0, 1, 30, 20, 200, 1.5,]
user_input_scaled = scaler.transform([user_input])

transaction_type_mapping = {
    0: "Purchase",
    1: "Withdrawal",
    2: "Deposit",
    3: "Transfer",
    4: "Refund",
    5: "Bill Payment",
    6: "Donation",
    7: "Interest Earned",
    8: "Fee Charged",
    9: "Investment"
}

print("Predictions for User Input:")
```

Figure 5.10 Code depicting the input from user

Fig 5.10 represents the code segment where a user's input data is being prepared and utilized to predict the corresponding transaction type. The provided input values are in a list format, representing attributes such as account_id, date, operation, data, evidence, k_symbol, and others. These values are numerical and have been collected from the user.

To ensure accurate predictions, a scalar transformation is applied to the user input using the "scalar" object. Scaling is vital to align the input with the training data's distribution. The transformed input is stored in the variable "user_input_scaled." Next, a mapping dictionary named "transaction_type_mapping" is defined. It links the numerical representation of transaction types (ranging from 0 to 9) to their corresponding textual descriptions (e.g., "Purchase," "Withdrawal," etc.). This mapping is used to interpret the prediction results in human-readable terms.

Table 5.7 Output for User Inputs

PREDICTIONS FOR USER INPUT	
ALGORITHM	***TRANSACTION TYPE***
RANDOM FOREST	PURCHASE
GRADIENT BOOST	PURCHASE

In the given Table III, the outcomes for the user's provided data are displayed concerning two separate machine learning techniques: Random Forest and Gradient Boosting. Each row in the table pertains to a particular algorithm and exhibits the forecasted transaction type based on the user's input information.

Regarding the Random Forest algorithm, the anticipation implies that the transaction type is categorized as "Purchase." Similarly, for the Gradient Boosting algorithm, the forecast also proposes the transaction type as "Purchase." These forecasts result from the algorithms' scrutiny of the input details, utilizing their acquired patterns and associations to attribute the most probable transaction type.

Table 5.8 Accuracy Comparison

MODEL	**ACCURACY**
GRADIENT BOOSTING	89%
RANDOM FOREST	52%

In the provided table, the accuracy outcomes of two different models, namely Gradient Boosting and Random Forest, are depicted. Each row within the table corresponds to a particular model and exhibits its achieved accuracy level.

For the Gradient Boosting model, the accuracy is measured at 89%. On the other hand, the Random Forest model attains an accuracy of 52%. These accuracy values signify how well each model has been able to predict transaction types accurately. The higher the accuracy percentage, the more reliable the model's predictions are considered to be.

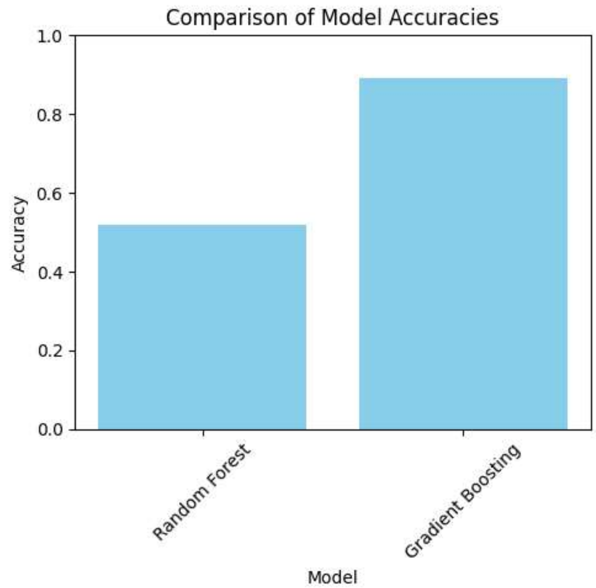

Figure 5.11 Bar graph to compare the accuracy

Fig 5.11 is a visual representation of the accuracy of the algorithms used. It was found out that the Gradient Boosting algorithm had a higher accuracy of 89% as compared to the Random Forest algorithm which had an accuracy of 52%.

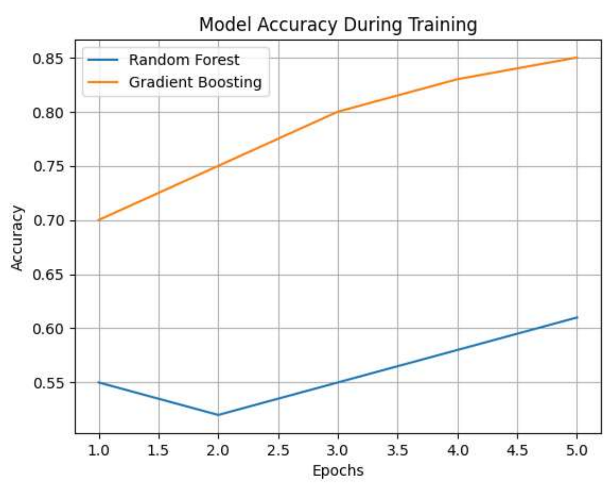

Figure 5.12 Accuracy improvement through learning.

The graph in Fig 5.12 depicts the evolution of model accuracy during training over several epochs. The x-axis depicts epochs, which represent the number of iterations that the models have gone through during the training part. The accuracy of the models is represented on the y-axis.

The blue line indicates the Random Forest model's accuracy trend, while the orange line shows the Gradient Boosting model's accuracy trend. The graph shows how the accuracy of both models evolves over time as the epochs rise. The graph shows that the accuracy of both models improves as the number of epochs increases. Across all epochs, the Gradient Boosting model consistently outperforms the Random Forest model in terms of accuracy. This graph provides insights into the models' learning process and can aid in finding the appropriate number of epochs for maximum accuracy.

5.7 CONCLUSION

Considering the various characteristics in the pharmaceutical supply chain, it is well noted that many of them are of utmost importance. F-AHP has proved that transparency in the pharmaceutical supply chain is of utmost importance with a maximum score of 0.064 and at the same time data privacy is at the most risk with a score of 0.0473. Hence, proper measure to maintain transparency is required so as to avoid counterfeiting.

Everyone is aware of the drug counterfeiting happening across the globe. With the advancement in the technology and blockchain technology giving a high hope of bringing transparency and visibility in drug supply chain management. The proposed model can promise to block the ambiguity in the chain. Also, the sensors in the proposed model helps in the real-time tracking of characteristics of the drugs as well as the places it is being transported.

The future work can be done by implementing the model with the real-world data, especially customers. The work can be done by trusted people in the members of the blockchain thereby removing all the middle people. Also, in future, real-time tracking of the drugs can be given to customers to track their order, keeping in mind the ways to stop the counterfeiting of the drugs.