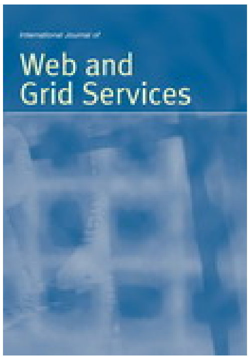

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Smart contracts and marketplace for just-in-time management of pharmaceutical drugs

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Abstract: Blockchain technology has recently been used to provide a secure storage environment through a distributed ledger. Blockchain has increasingly been used in other sectors such as real estate and supply chains, where trust and transparency are paramount considerations. In the pharmaceutical industry, for operational efficiencies, information must be shared reliably between the various stakeholders. A significant limitation in the existing literature is the lack of work to address niche problems such as the just-in-time disposal of drugs that are close to expiry. To address this gap, we propose using blockchain technology. The architectural underpinning of the proposed system (PharmaBlock) is presented and discussed. The primary contribution of this paper is the use of an early warning system (EWS) coupled with marketplace to intelligently identify and dispose of near-expiry drugs. The EWS and marketplace are evaluated and benchmarked using an experimental setup. The result of this experimental has shown that over 90% of notifications were sent correctly and shown also more than 92% of the optimal prices were predicted correctly in PharmaBlock.

Keywords: blockchain; smart contracts; early warning system; e-marketplace; pharmaceutical supply chain; research challenges.

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1 Introduction

The top priority in any healthcare system is the delivery of medicine as a strategic product. Currently, one of the most significant research challenges is managing and optimising pharmaceutical supply chains (Uthayakumar and Priyan, 2013; Franco and Alfonso-Lizarazo, 2020). The pharmaceutical industry faces several problems, such as finding the right balance between producing medicines to meet demand, tracking every unit in the supply chain, reducing the number of counterfeit medicines (Rossetti et al., 2011), and managing medicines that are about to expire. The number of counterfeit medicines is increasing due to the lack of traceability and the imperfect supply chain system. This problem lies in a lack of shared information between nodes in the supply chain, for instance, manufacturers are often not able to track their products after exporting their drugs (ten Ham, 2003). Hence, better tools are needed to manage information on medicine.

The risk to human life due to the counterfeit medicines available on the global black market is becoming an issue of great concern. Developing countries in Africa and Asia are severely affected by counterfeit drugs, which account for around 30% of total drug sales (Cartwright and Barić, 2018). To control the problem of counterfeit medicine, it is necessary for pharmaceutical companies and distributers to have a very secure system to track and trace every entity on the supply chain (Chircu et al., 2014; Yu et al., 2010).

A survey by Supply Chain Management (SCM) World, the world's top 20 pharmaceutical companies make total sales of about $ 496 billion per year and the gross value of drugs that must be destroyed due to decay is about $10 billion (Bekker et al., 2018). SCM World has worked with the Future of Healthcare Advisory Board to quantify the amount of medicine that is wasted annually. The importance of analysing this data is to outline how to reduce the number of over-the-counter medications that are wasted due to expiry which has negative consequences on the economy (Abou-Auda, 2003; Mirdad and Hussain, 2022).

There are five steps in the pharmaceutical supply chain to ensure that a drug inventory is available for distribution to providers and patients. First, drugs originate in manufacturing sites. Second, medicines are transferred to wholesale distributors. Third, drugs are stocked in retail outlets or pharmacies. Fourth, drugs are subject to price negotiations and processed through quality and utilisation management screens by pharmacy benefit management companies. Fifth, drugs are dispensed by pharmacies and delivered to and taken by patients (Kim and Laskowski, 2018). Over the past few years, different technologies have been used in pharmaceutical supply chains to improve the performance, quality, security, and visibility of the supply chain. Currently, several solutions have been proposed in the literature to enhance the visibility of pharmaceutical supply chains and to track and trace medicines using automatic identification (Auto-ID) technologies to secure pharmaceutical supply chains with passive radio frequency ID tags, and transparent containers with sensor nodes as described in several studies (Papert et al., 2016; Yue et al., 2008). Other studies used machine learning classifiers and IoT mechanisms. These solutions ensure temperature maintenance and a reliable and secure infrastructure (Konovalenko and Ludwig, 2021; Safkhani et al., 2020). Even when using these technologies, there are still many uncontrolled issues that negatively impact the supply chain workflow. The currently used technologies can characterise and classify the vital nodes of the pharmaceutical supply chain to be centralised including manufacturers, wholesale distributors, and pharmacies. Currently, the data is stored and/or managed by large manufacturers and pharmacy retails using their own centralised system. As a consequence, centralised networking in an important sector like pharmaceuticals takes time and energy to handle medicines, however, in some cases, drugs are not handled properly. Additionally, despite the technologies that are being used, transparency and visibility over the pharmaceutical supply chain is still lacking. Tracking every item from end-to-end is almost impossible with the currently used technologies. Pharmacy retailers or end-users have not yet found a smart system that can help them sell all nearly expired drugs and obtain a benefit.

To address this issue, the introduction of blockchain technology can reap several benefits. Blockchain technology provides a secure environment that is immutable, consensus-based and transparent in the finance technology world. Efforts have been made to apply blockchain to other fields where trust and transparency are needed (Zheng et al., 2018). The reliable sharing of pharmaceutical information between various stakeholders is essential. The use of blockchain technology adds traceability and visibility to supply chains like pharmaceuticals and enables information to be provided from end to end. Drugs, for example, can be tagged and scanned for secure storage in a distributed ledger which is updated in real time as drugs are transferred from one entity to another in the supply chain (Nofer et al., 2017). Researchers have defined blockchain as a digital distributed ledger containing valuable data and information that can be shared over the network which forms a series of recorded valid transactions in chronological order (Halpin and Piekarska, 2017). Transactions are registered in a public, secure, and permanent ledger with a timestamp and a number of other details.

Applying blockchain technology to pharmaceutical supply chains enhances and improves different parts of the supply chain architecture (Saberi et al., 2019; Bocek et al., 2017):

- *Provenance tracking:* In supply chains such as pharmaceuticals which comprise a huge number of elements, it is almost impossible to trace and track every record. This leads to a lack of transparency and as a consequence, will increase the cost of the pharmaceutical supply chain, negatively affecting customer relations and will ultimately damage the drugs' brand. In blockchain-based supply chain management, historical records on drugs are kept forever and can be traced through the blockchain from its origin to the final user, or to where it is at this moment and tracking product information becomes easier with the help of embedded sensors and RFID tags. Blockchain can reduce delays in delivery as drugs can be tracked in real time and the risk of misplacement is rare (Kim and Laskowski, 2018). Moreover, to detect fraud in the pharmaceutical supply chain, provenance tracking can be used (Neisse et al., 2017).

- *Cost reduction:* According to a survey of supply chain workers conducted by the American Productivity and Quality Centre and the Digital Supply Chain Institute (ElMessiry et al., 2019), more than one-third of people interviewed stated that using blockchain technology in any supply chain can reduce the overall cost of tracking products through the supply chain in real time and the security of each transaction is guaranteed.
- *Establishing trust:* Trust in complex pharmaceutical supply chains with many participants is required for smooth operations. Applying blockchain technology to pharmaceutical supply chains increases trust between different nodes in the pharmaceutical supply chain because the immutable nature of blockchain is well-designed to prevent tampering and therefore trust is established (Schöner et al., 2017).
- *Interoperable:* Blockchain allows the data to be more interoperable between pharmaceutical supply chain nodes. As a result, it is easier for companies to share information and data with different stakeholders such as manufacturers, suppliers, and vendors (Bell et al., 2018).

Accordingly, there is a need to design an intelligent system to decide when to purchase a product, when to sell a product, and for what price to sell it. Furthermore, to address the gaps mentioned above, there is a need for an intelligent system (based on blockchain for provenance) to generate alerts for pharmacy retails to warn them that certain drugs are about to expire. Furthermore, as a part of the generated alert, the EWS provides the pharmacy retails with the option to sell expiring drugs. The EWS is part of the AI layer within PharmaBlock that interacts with the blockchain platform. This alert system provides alerts and makes recommendations.

A decentralised marketplace has many advantages in terms of improving the efficiency of marketing. A traditional online marketplace has several limitations such as security and privacy issues, high maintenance costs, and a lack of transparency. On the other hand, a decentralised marketplace based on blockchain technology offers a secure and trusted environment. A decentralised marketplace using an intelligent decision-making approach such as the just-in-time inventory system provides consumers with a highly secure environment and helps to achieve one of the main objectives of this study, which is to reduce the wastage of drugs by selling medicines which are about to expire to other consumers like pharmacies in the marketplace. This system will reduce costs by minimising the need for warehouse storage space. This marketplace will receive over-the-counter drugs that are about to expire and display them in the decentralised marketplace to sell them at an optimal price. Online markets connect buyers and sellers of physical products over the Internet. These marketplaces also offer payment services that make it easy for consumers to pay for purchases (Lancastre and Lages, 2006). However, online marketplaces require consumers to pay an extra fee to the platform if a product changes hands and a third-party payment system is used (Chang and Wong, 2010). Furthermore, the buyers' personal data can be hacked or stolen, which makes a traditional marketplace untrusted. Physical marketplaces can sell over-the-counter drugs for a lower cost which means consumers save money and manufacturers increase their revenue by influencing customers through product recommendation (Subramanian, 2018). Developing a decentralised marketplace has become a necessity to enhance and increase network services and recommendation systems for goods, and to simplify transactions between peer-to-peer in a trusted manner (Jøsang et al., 2007; Shen et al., 2010).

The structure of this paper is as follows. Section 2 presents the related work on the blockchain platform-based pharmaceutical supply chain. In Section 3, a framework named PharmaBlock is proposed as a platform service and its related components are discussed. Section 4 presents our PharmaBlock modelling and how we collect and classify PharmaBlock information intelligently. Sections 5 and 6 detail the workflow of our intelligent date-based early warning system and the workflow of the PharmaBlock decentralised marketplace respectively. Blockchain has been used in our work to enable provenance. The primary contribution of this paper is discussed in Sections 5 and 6. Sections 7 and 8 detail the experiments on both the early warning system and the decentralised marketplace. A discussion and the results of the experiments are provided in Section 9. Lastly, Section 10 concludes the paper and suggests future research directions.

2 Related work

The main focus of this section is to survey the existing literature to find the issues and challenges related to pharmaceutical supply chain information in sharing data between various entities in the supply chain using blockchain and to provide an intelligent solution for stakeholders and consumers to reduce drug wastage and obtain a benefit when using the drug decentralised marketplace. The scope of this review is limited to work which surveys the existing literature with a view to identify and formulate the problems in the existing literature by adding features to benefit every entity in the supply chain. Thus, in this section, we review the recent literature that identifies the uses of blockchain in pharmaceutical supply chain management, its challenges, and solutions. The papers identified cover issues related to blockchain-based approaches for pharmaceutical supply chains. The selected papers identify the challenges related to blockchain, thus by analysing them critically, we provide a synthesis of the state-of-art on pharmaceutical nodes in the supply chain, the challenges and various solutions using blockchain technology.

In a study by Hulea et al. (2018), the authors represented the architecture of a platform for cold drug supply chain management and solutions and explained the framework of cold pharmaceutical chain using a Hyperledger distributed ledger. This work explains how the transaction is stored and how the delivered products and the associated environment data are tracked. The authors of this work used the Sawtooth framework developed by Intel to collaborate and to track products using a scalable infrastructure. Participation in the cold chain network requires each participant to join the network with one validator node.

The work in Bamakan et al. (2021) addressed how blockchain technology meets the requirements of a pharmaceutical cold supply chain such as pharmaceutical digital identity, serialisation and traceability, data integrity, transparency, and waste management. This work also discussed the main benefits and drawbacks of the pharma cold chain and described several cases where blockchain features were employed in their projects.

The work in Haq and Esuka (2018) explains the use of permissioned blockchain technology to add traceability and visibility which means to provide all the information over drug distribution to drug manufacturers and drug regulatory authorities, and also to add security to the pharmaceutical supply chain from manufacturers to consumers. Moreover, this study shows the positive effects on the patients after they used the drugs which was recorded on a database for future statistics.

In Alangot et al. (2017), the author proposed a novel blockchain technology combined with the IoT framework called the Global Data Plane, which can help in communication and the management of data between different nodes. This proposed system builds a high trace and track level of a scalable and trusted system for the pharmaceutical industry by modelling a large infrastructure IoT-scale system. In this work, the authors implemented this system using Tendermint which is divided into two components: a blockchain consensus engine and a generic application interface.

In Bocek et al. (2017), the authors presented a framework called modum.io AG using a combination of IoT and blockchain technology to ensure data immutability, while reducing the costs in the pharmaceutical supply chain. The main goal of this work is to give detailed insights into how modum.io AG uses blockchain technology in the area of pharmaceutical supply chains using smart contracts to automatically measure the temperature through the supply chain without tracking any other important factors in the pharmaceutical supply chain.

Uddin (2021) proposed a novel track and trace pharmaceutical system called Medledger based on a Hyperledger Fabric blockchain platform to solve the problem of transferring and tracking drugs. The main goal of the proposed system is to allow stockholders to securely execute and record transactions over the pharmaceutical supply chain to enhance integrity and reliability and also to provide maximum transparency and traceability in the system. This decentralised framework allows only participants who authenticate themselves using digital certificates to access it.

The work in Abbas et al. (2020) presented a framework of blockchain and machine learning-based pharmaceutical supply chain management and a recommendation system. The authors of this work proposed a system with two modules: blockchain-based drug supply chain management and a machine learning-based drug recommendation system for consumers. The first module tracks and traces the drug delivery process in the smart pharmaceutical industry. In the second module, the authors used N-gram and LightGBM models to recommend the top-rated drugs for customers. In this work, the authors stated that the proposed system can help pharmaceutical companies eliminate the problem of counterfeit drugs.

The work in Musamih et al. (2021) investigated the challenges of tracking drugs within the supply chain. The authors proposed a blockchain-based solution to enhance the tracking and tracing of drugs in a decentralised manner. The authors used the Ethereum blockchain platform to achieve automated accessibility for the recorded transactions made by participants. The proposed system architecture allows the stockholders to interact with the smart contract to access data on-chain. This work was tested and validated and it also discussed the cost and security analysis of the proposed solution.

Akhtar and Rizvi (2021) proposed a solution for pharmaceutical supply chain traceability using blockchain technology. The authors used Ethereum and Hyperledger

Fabric platforms and compared the performance of the two approaches under the use case of the pharmaceutical supply chain. After comparing the two different approaches, the authors found that the Hyperledger-based approach is more efficient in terms of scalability, security, and it is more enterprise friendly. Unlike Ethereum, accountability in the public blockchain in Hyperledger is easier to achieve as the authors stated in this work.

The architecture in Ouf (2021) introduced a framework that enhances security in the pharmaceutical supply chain, improve transit and storage, and improve patient satisfaction and trust. The author of this work combined the Internet of Things, the Semantic Web, and blockchain to increase the transparency and visibility of the pharmaceutical supply chain. The proposed architecture of the pharmaceutical supply chain-based semantic blockchain comprises three layers. The first layer is the IoT to represent hardware and wireless sensor networks as well as RFID, the second layer is the Semantic Web which represents the knowledge, relationships, and transactions of IoT and the blockchain, and the third layer is the semantic metadata to annotate all the objects and data types.

The work in Sabah et al. (2022) introduced a new system to detect counterfeit drugs in the pharmaceutical supply chain by adopting a Hyperledger Fabric platform. This peer-to-peer framework-based smart contract makes the process of delivering drugs to patients more secure and much faster. The authors of this work divided the proposed framework into four parts: the ingredient verification process to ensure the authentication of each element, the drug sample verification process to ensure the authentication of each drug, the QR code and drug delivery verification process, and the observation and revoke process. These four steps of the proposed solution verify the medicine before and after production.

The proposed framework solution in Pandey and Litoriya (2021) describes the process of delivering drugs in the drug supply chain with a high level of transparency. The proposed work is based on recording the logistic requirements of drugs on the blockchain platform from the starting point of supply chain manufacturing to delivery to the patient. Hence, if any counterfeit drugs are introduced to the supply chain, they will be rejected by the proposed system. The decentralised framework has 11 computational nodes and is based on the Hyperledger Fabric platform. The proposed system was tested and compared with three other systems, namely the conventional system, the system proposed by Vledder et al. (2019) and the system proposed by Mouaky et al. (2019).

Ehioghae et al. (2021) proposed a verification system that is able to enhance the tractability of drugs in the supply chain. They used two germane smart contracts namely: shiDrug and receiveDrug to ensure the system moves drugs safely over the pharmaceutical supply chain using Hyperledger Fabric. Only valid actors in the supply chain can execute smart contracts, while the final customers are able to verify the drugs using a unique identifier. The authors of this work implemented the proposed system in three parts: blockchain development, API development, and user interface development. The proposed system was evaluated based on transaction throughput, latency, and resource consumption.

The work in Agrawal et al. (2022) presents a framework that allows manufacturers to monitor drugs in the supply chain to improve transparency. The work also minimises both cost and time with a focus on transferring drugs forward and backward in the supply chain. The forward chain works in a similar way to any traditional pharmaceutical supply chain, while the backward supply chain focuses on managing the supply chain in case of a drug recall. The contributions of this work are increasing the transparency for the pharmaceutical supply chain and reducing both cost and time. The authors of this work used the Hyperledger blockchain to implement their proposed work.

Tseng et al. (2018) suggested the use of a Gcoin blockchain framework, a governance model of the drug supply chain, to improve transparency, the efficiency of information exchange, and to protect data in the drug supply chain with an open government organisation. The main aim of this work is to transform the centralisation by government to a decentralised system which uses every participant in the network to improve the efficiency of information exchange in combination with an open government and decentralised autonomous organisation (DAO) regulation model to ensure a secure and transparent drug supply ecosystem.

The work in Ahmadi et al. (2020) merged IoT technology with blockchain and implemented it in the pharmaceutical supply chain to reduce the amount of counterfeit drugs. The authors of this work investigated novel pharmaceutical governance based on IoT and blockchain technology, which is a type of distributed ledger technology that maintains an immutable record of all transaction information. The authors state that implementing an IoT-based blockchain system provides the tools for the pharmaceutical industry to improve drug governance along the supply chain and as a result, makes healthcare more efficient and reliable.

Based on the literature review, we identified the following significant challenges in using blockchain to enhance the services in a drug supply chain. The contribution of this paper to the existing literature body is the use of bespoke artificial intelligence (AI) algorithms for operational efficiencies on top of the pharmaceutical blockchain. In particular, we propose and evaluate smart contracts for

1. A personalised early warning system to detect and push them to the marketplace. None of the existing studies take into account how pharmacies can benefit by establishing a decentralised marketplace for selling and purchasing nearly expired drugs using blockchain technology.
2. Predict an optimal selling price for drugs.

The significance of this work is discussed in Section 1.

3 Proposed framework of PharmaBlock

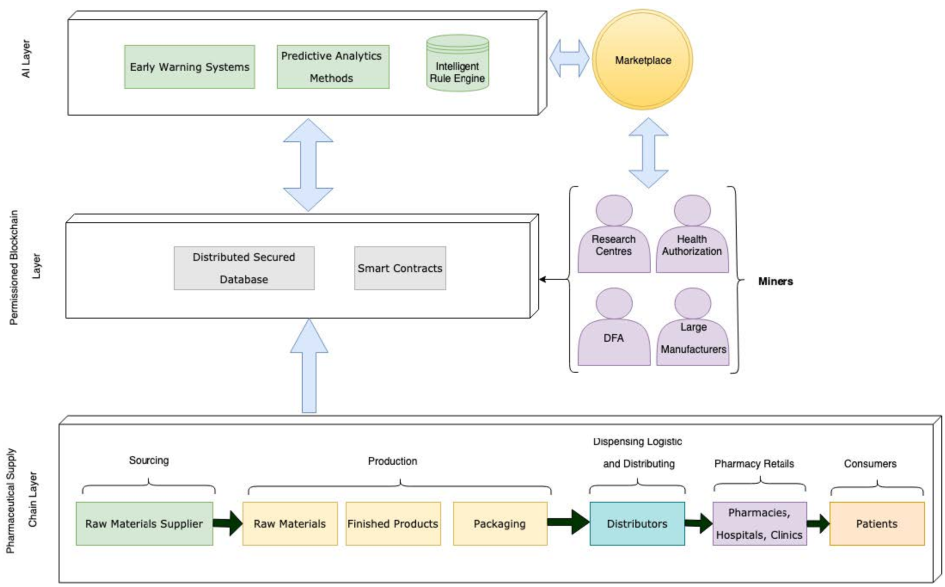
To address these problems, we present the architecture of the PharmaBlock framework as the base of the data flow of pharmaceutical supply chain information to create transparent drug transaction data. In particular, the key aspect of PharmaBlock is that it has the ability to identify just-in-time medicines which are about to expire and dispose of them using the decentralised marketplace. In this paper, various artificial intelligence algorithms are used to develop an intelligent solution to the drug wastage issue. It is important to note that this paper adapts a pharmaceutical supply chain and applies an intelligent mechanism using blockchain technology. We also propose intelligent methods to model the overall workflow of the drug supply chain on the fly. Then, we evaluate the performance of various AI methods and select an optimal combination.

In the current literature, there is no model that uses artificial intelligence techniques to store pharmaceutical supply chain information on the fly to make decisions and control entities from end to end. In this research, we investigate the use of AI methods to address the aforementioned research issues and make decisions intelligently. The intelligence built into PharmaBlock provides automated and reliable mechanisms to achieve the following:

- classify the stored data in order to allocate and give different accessibility levels for data
- alert pharmacies to accelerate the process of selling nearly expired drugs
- determine an optimal selling price for a drug in a decentralised marketplace.

The architectural framework for PharmaBlock is shown in Figure 1.

Figure 1 Architecture of PharmaBlock (see online version for colours)



PharmaBlock captures and stores the data originating from the entire pharmaceutical supply chain. This study (Mirdad et al., 2023) has explained in details the working of PharmaBlock framework. PharmaBlock has five entities as described below:

- *First entity: pharmaceutical supply chain layer* – The pharmaceutical supply chain has five stages: sourcing, production, distribution, pharmacy retails, and the final consumers which are part of pharmaceutical supply chain. This is a generic representation and any pharmaceutical company wants to join the permissioned blockchain layer can do so if they have permission to join.

  The information that captured is the name of the drug, the manufacturing location, date and time stamp, the number of stock keeping units (SKUs) which is a number assigned to a product by a retail store to identify the price, product options and manufacturer and it is used to track the inventory in a particular store (Shekar et al., 2019). In this way, only the details of certified and well-known manufacturers or medical companies are stored in the blockchain. PharmaBlock is a consortium blockchain. As such, any drug manufacturer can register and enrol to be part of PharmaBlock. However, their membership needs to be approved by the consortium by majority consensus. Once a pharmaceutical company is part of PharmaBlock, it will be provided with APIs or a mechanism to provide data.

- *Second entity: permissioned blockchain layer* – A key layer in PharmaBlock is the permissioned layer. The Ardor blockchain platform is chosen to develop this PharmaBlock platform as it provides the ability to define a parent-child chain. Ardor is a multichain blockchain platform with a unique parent-child chain architecture. The security of the whole network is provided by the parent Ardor chain while the interoperable child chains have all the rich functionality (Jelurida, 2016). Within the permissioned layer, our system collects the incoming information streams from the pharmaceutical companies and passes it to the intelligent rule engine for further processing and classification. The permissioned blockchain layer contains a smart contract which is an entity that interacts with the permissioned blockchain layer and other entities of PharmaBlock. It plays a very important role by checking the accessibility of other nodes and miners in the permissioned blockchain layer and to finalise payment in the marketplace and store values for the selling point prices of the drugs.
- *Third entity: miners* – Our proposed conceptual framework is designed to include four miners at this stage. If the work requires additional miner/s, they can join the network as required. For the process of joining the PharmaBlock and to ensure all miners and nodes are trusted, the process of identity and access management must be followed. Authorised miners who have already joined the PharmaBlock network can give permission for a new miner to join by majority consensus and using identity and access management processes for the majority consensus of existing miners. The newly joined miner will be 'labelled' as a trusted node. Miners are eligible to access information stored in the PharmaBlock using a smart contract depending on their need for this information and their level of accessibility. One of the miners is the Health Authority, which is an organisation responsible for providing strategy to improve pharma health services, identify pharma needs, and monitor the development of health services in general. Other miners such as the DFA, research centres, and large manufacturers can help improve the pharmaceutical field, increase efficiency and advancement, and oversee the workflow of producing and manufacturing medicines.
- *Fourth entity: distributed marketplace* – The distributed marketplace is a mechanism where people can sell just-in-time drugs which have nearly expired. The marketplace platform is designed for permissioned users only as we want to deal only with authorised information. It is meant to be a marketplace and hence only authorised users who are part of PharmaBlock can provide a listing; however, it should be open to anyone to make purchases using a smart contract. Briefly, the marketplace is for pharmacy retails to dispose of their nearly expired drugs at an optimal price whenever they wish to sell.

- *Fifth entity: AI layer* – The AI layer has predictive analytical methods on top of the permissioned blockchain layer and it also has an EWS and an intelligent rule engine repository. The following points briefly describe each entity in the AI layer:

  1. The intelligent rule engine: The intelligent rule engine's main role in the AI layer is to receive standard description information from the blockchain layer for all drugs. This medical description includes the name of the drug, drug ID, batch ID, quantity produced and expiry date, etc. Further more, the intelligent rule engine works intelligently and associatively with the smart contract to intelligently carry out the classification of the incoming information stream. Then, the entered information is intelligently classified as public, private, or semi-public data depending on the attributes of the information and preferences of the pharmaceutical companies.
  2. Early warning system: The role of the EWS (within the AI layer) is to intelligently and proactively generate personalised alerts for the pharmacy retails using PharmaBlock. The alerts correspond to expired drugs. Furthermore, as part of the generated alert, the EWS provides the pharmacy retails with the option to sell drugs which are about to expire. The EWS is part of the AI layer within PharmaBlock that interacts with the permissioned blockchain chain.
  3. Predictive analytical methods: Predictive analytical methods are intelligent methods to predict an optimal selling point to sell drugs, as well as to predict the drugs future demand based on population statistics.

4 Modelling PharmaBlock, intelligent information collection and classification

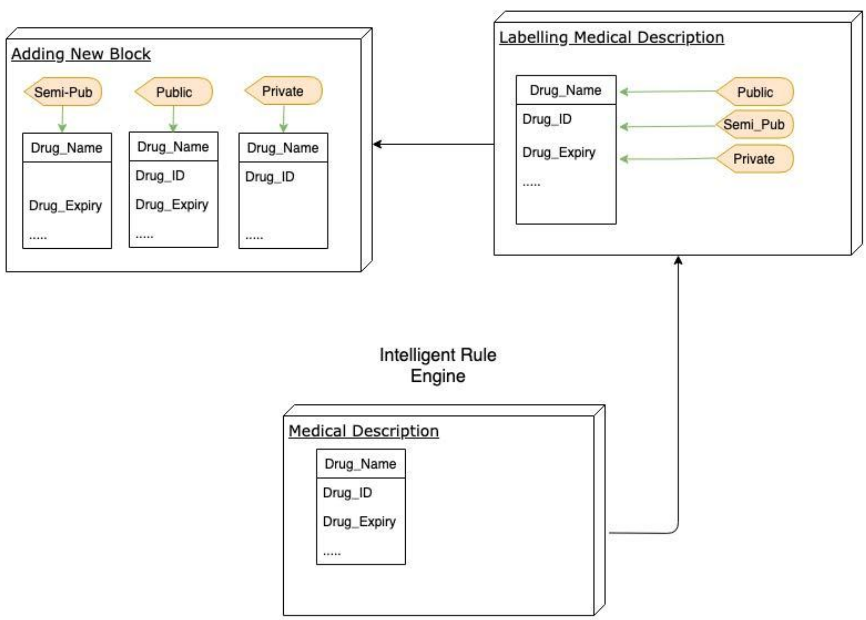
The following steps represent how PharmaBlock classifies pharmaceutical information:

1. The entry of incoming streams from the pharmaceutical supply chain layer is intelligently classified and labelled by the intelligent rule engine and smart contracts into three different categories at the entry stage to allow different levels of accessibility: public data, semi-public data, and private data
2. Permissioned users (miners and nodes) in PharmaBlock can access different types of permissioned data depending on their access privileges.
3. Drug owners can specify accessibility to drug information using the smart contracts by following the sub-chaining architecture. Smart contracts organise the owner's access process to the private and semi-public blocks for eligible nodes only.
4. The public classified data is stored in the public block, and the private and semi-public data can be stored using the two sub-chains.

All data in the medical description which is stored in our PharmaBlock system must be classified for easy access whenever it is needed. The following approach for classifying data is illustrated in Figure 2.

- *Stage 1:* Information gathering (medical description) – all data is collected by the intelligent rule engine from the pharmaceutical supply chain layer. The medical description must have standard information to be accepted and uploaded as a pending transaction in the blockchain layer, such as: drug ID, drug expiry, drug name, etc. This standard information will help our system to intelligently store data to the relative chain later, as shown in Figure 2. Different drug companies may have different drug IDs or names for the same medical component. This may lead to drug ID duplication. To avoid this problem, our system provides a list of drug IDs to choose from and if a particular ID is not on the list, the drug company can request to add a new drug ID which will be checked via a consensus mechanism for approval.
- *Stage 2:* Classification and labelling information (medical description) – in this stage, the intelligent rule engine labels the information received in the medical description and refactors it into three groups, as previously discussed, to be stored in the relevant chains.

Figure 2 Architecture of classification (see online version for colours)



5 Workflow of early warning system in PharmaBlock

In this section, we present our intelligent alert system mechanism to predict alarm notifications to alert pharmacists about drug expiry prior to expiry time using supervised machine learning. To present the end user with intelligent and bespoke time-based alarms alerting them to drugs expiry, we propose a warning system. The date-based early warning system (DBEWS) provides alerts and recommendations (Berg et al., 2005). The working of the warning system to generate alerts to warn the end users about the impending expiry of drugs is as follows:

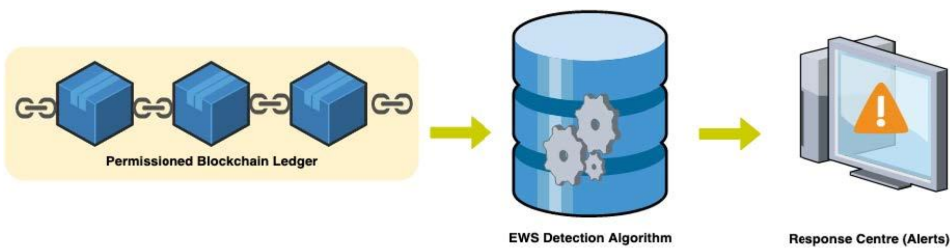
a automatic detection of all drugs stored in the blockchain attached with some required information such as: drug expiry date and number of batches and it determines their locations

b automated alerts to be sent to the pharmacy retails when it is needed.

This is achieved by extracting drug information from the PharmaBlock permissioned blockchain layer which is then analysed and an alert is sent to the pharmacies if these drugs will expire in a certain period of time, depending on the personalised value entered by pharmacy retails. At this stage, we setup a timeline that can use a personalised variable value to generate alerts to a pharmacy, where every end-user sets their preferred time window. This personalised variable value will generate alerts and will vary for each pharmacy to let the pharmacy retails know in enough time when a drug will expire to ensure these drugs can be sold prior to expiry. The DBEWS reminds pharmacy retailers when the currently stored drugs have nearly expired, providing a proactive solution so these drugs can be sold instead of them going to waste.

This paper is the first to use a DBEWS in pharmaceutical supply chain management. This model takes this variable value and compares it against the expiry of the drug batch; if it is within this period, it automatically generates an alert to the end user. Figure 5 shows the proposed DBEWS.

Figure 3 Early warning detection module (see online version for colours)



The proposed DBEWS comprises three components, as shown in Figure 3.

- First stage: Customer activates the DBEWS and provides a personalised value for each drug.
- Second stage: PharmaBlock uses the intelligent DBEWS Algorithm 1 to find drugs using a personalised value. The proposed algorithm for the DBEWS is applied to PharmaBlock to identify when to generate alarms.
- Third stage: DBEWS generates alerts and sends these to the client.

Once this case has applied, DBEWS generates a transaction on PharmaBlock and sends a notification to pharmacy retailers, informing them of the drug's expiry date and the importance of disposing of these drugs to other pharmacies, hospitals and customers and provides recommendation on ways to dispose of them.

Algorithm 1 Early warning date-based algorithm

```
Begin
Store V in the blockchain
Repeat for every batch in the blockchain
Compare V with current date
if V > current date value then
  EWDM (V, R, A)
end
else
  Generate an alert A
end
else
  Send a recommendation
end
Stop
```

6 Workflow of decentralised marketplace in PharmaBlock

An e-marketplace is a mechanism where people can sell their products in real time under the control of a third party. Blockchain technology enables sellers and buyers to transact in a trusted environment where the role of the third party is not needed. In this paper, the main purpose of developing an e-marketplace is to display just-in-time drugs which are close to expiring. The e-marketplace platform is designed for permissioned users only as we only want to deal with authorised information, hence only authorised users who are part of the PharmaBlock platform can provide a listing; however, it should be open to anyone to purchase using a smart contract. Briefly, the marketplace is for pharmacy retails to dispose of their nearly expired drugs at an optimal price whenever they wish to sell. The marketplace interacts with the PharmaBlock platform by extracting the basic information required to dispose of the drugs, such as how many batches are available for sale? and what is the selling price?

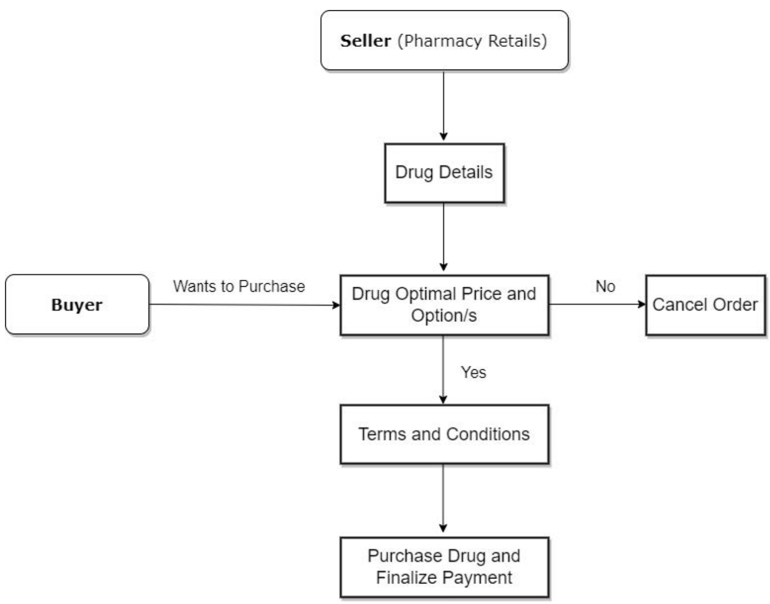
A decentralised marketplace is an online e-commerce platform that is executed on the blockchain. This marketplace targets the pharmacy retail outlets who want to sell multiple batches of drugs prior to their expiry. While only registered users are allowed to sell pharmaceutical drugs using the marketplace, both registered and non-registered users (including general consumers and patients) are allowed to use and access this marketplace as long as they have already joined this permissioned blockchain network. The workflow of the marketplace is illustrated in Figure 4.

The marketplace has an intelligent decision-making centre which provides recommendations on the optimal price to sell the drugs. The generated recommendations are based on the following factors: the previous price point for which the drugs were sold, the number of other similar drugs being sold on the PharmaBlock platform and the number of customers who are viewing the advertisement. The price prediction module in the marketplace takes this input and provides recommendations on the optimal selling price. To facilitate this process, the decentralised marketplace is set up in two steps:

- *Building up the decentralised marketplace:* We build a marketplace-based blockchain, where if someone wants to sell a drug, we can create a new block that is referenced or linked to the original blocks for the drugs, then the drug information is copied from the original blocks and stored. This sets it up as a transaction in the marketplace and every transaction that takes place in the marketplace will create a block that is linked to the original source information.

- *Data exchange:* The decentralised marketplace uses the blockchain platform as an enforcer of rules and also as a trusted party between sellers and buyers. The drug marketplace consists of two players: buyers and sellers, who must have public and private keys to exchange data securely and to match sellers with buyers. Additionally, smart contracts are used to share data in the marketplace to ensure the privacy of buyers and sellers and also to ensure their authority and accessibility to different levels of information in the blockchain. To exchange data between buyer which in our case is the patient, and the seller which is a pharmacy retail, the seller provides encrypted data to be added to the block in the marketplace and then sends the encryption key directly to the buyer. The buyer buys the products and then sends the cryptocurrency to all honest parties in blockchain.

Figure 4 Marketplace workflow



The following steps comprise the process workflow of selling drugs in the marketplace, as shown in Figure 5:

Stage 1 Send information to the marketplace's blockchain: During this step, when a pharmacy retail wishes to dispose of drugs, the public description of the information corresponding to the drugs is encapsulated and stored as a new block. The marketplace is given access to the new block. Once this has occurred, the information in the new block is made available on the marketplace.

Stage 2 Users access to the marketplace: Consumers in the marketplace must register to access the marketplace and the information available in the marketplace. Once a user has been registered, then s/he is able to view the information in the marketplace.

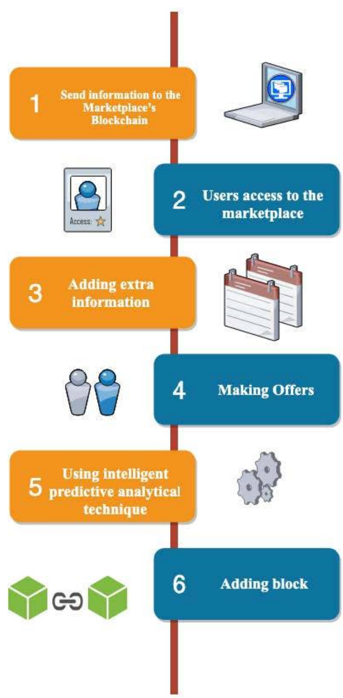
Stage 3 Adding extra information: The seller can add extra information to the newly created block that is needed for the selling process such as: seller information, seller location, number of available batches, selling and base selling price.

Stage 4 Making offers: Multiple consumers visit the marketplace and view the listing. They can make offers on the listings.

Stage 5 Using intelligent predictive analytical techniques: It is at this stage post the listing of the drugs, the price prediction module (PPM)'s role comes into play. The PPM will use the multiple factors discussed above as input to the simple linear regression, random forest regression, and support vector regression to determine the optimal selling price.

Stage 6 Adding a block: The seller decides which buyer the product will be sold. Once the payment for the sale is made, the seller's details are added to the block in the blockchain and also which buyer bought the product. Once the payment is made, the pending block will be added and confirmed on the blockchain as a permanent transaction.

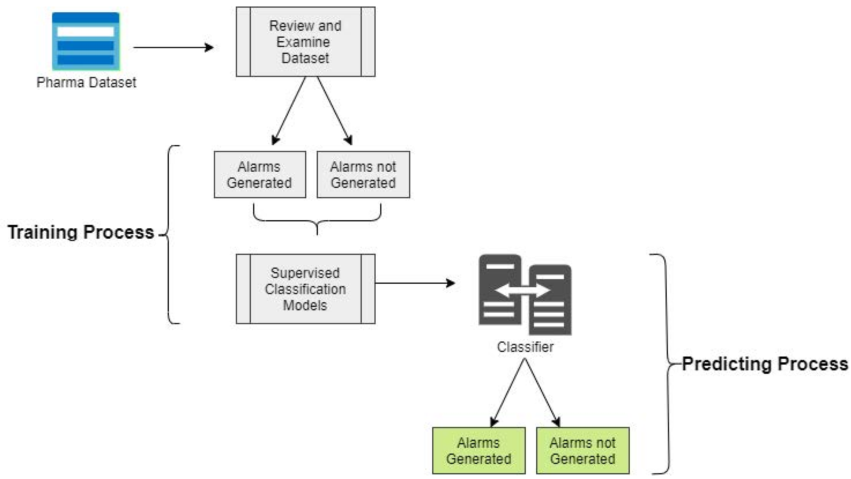
Figure 5 The process workflow of selling drugs in the marketplace (see online version for colours)



7 Experiment setting for early warning system

In this section, we present our mechanism for predicting the alarms which should be generated to notify the pharmacists prior to drug expiry using supervised learning, as shown in Figure 6.

Figure 6 The experiment framework for EWS (see online version for colours)



Our model consists of three phases: collecting data and preparing the dataset, the training process, and the predicting process. First, we collected information from our PharmaWeb server. The dataset consists of several columns such as: drug-name; user-ID; notifications; drug-expiry-date. The dataset also consists of about 1,000 records with multiple users. Then, we examined the dataset manually to ensure the quality of the data and we also captured the generated alarms and documented them manually. Second, we trained different algorithms using the training dataset using drug-expiry-date as input. Third, we tested our models for the evaluation and to examine their ability to predict.

In this experiment, we split the dataset into training set comprising 70% of the data and a testing (or validation) set containing the remaining 30%. During the training process, the model learns from the training data, iteratively optimising its parameters to minimise the prediction errors. This phase involves employing various algorithms to capture underlying patterns and relationships within the data. The model's performance is then evaluated on the testing set, unseen during training, to assess its generalisation capabilities. This separation of data into training and testing subsets helps gauge how well the model can predict on unseen data, providing essential insights into its effectiveness and potential overfitting. Striking the right balance between training and testing data allocation ensures the model's ability to make accurate predictions on real-world data beyond the training dataset.

In this experiment, we applied six supervised algorithms, namely generalised linear regression, logistic regression, deep learning, decision tree, support vector machines, and naive Bayes model. A brief description of each algorithm is as follows:

- *Generalised linear model/classifier:* The generalised linear model (GLM) differs from other models by its ability to test nonlinear models in the context of regression. GLM is a mathematical framework and is a supervised classifier mechanism. This model is widely used because of its natural approximation for complex functional relationships and it is straightforward in terms of estimating unknown parameters (Myers et al., 2012). In this study, we applied the generalised linear model to our dataset using the RapidMiner platform and the performance of this model is shown in Tables 1–5. The expected output is a classifier model that will determine the exact time to generate the alerts.

- *Logistic regression/classifier:* The logistic regression model is used for binary classification problems (two class values) and is widely used in medical fields to predict mortality in injured patients. This model has a huge number of applications as described in Allison (2012). In this study, we have made use of the logistic regression model using RapidMiner to divide the dataset output into two groups of predictions that tells us whether the alarms have been generated or not. The performance of this model is described in Tables 1–5.

- *Deep Learning/classifier:* The deep learning model is a deep neural network that is trained to extract features from a large group of examples to assign labels to textual units. It has been proven to be powerful in mimicking human skills. It has a wide range of applications as detailed in Sameerunnisa et al. (2017). In this study, the deep learning algorithm is used for text classification and we designed and applied the deep learning model in RapidMiner to build the classifier. The performance metrics results of this model are shown in Tables 1–5.

- *Decision tree/classifier:* The decision tree model has a root at the top and grows downwards. This algorithm splits the dataset into segments, small branches, and all segments form the decision tree. This model has been widely used for data mining and text classification, as in Quinlan (1986). In this paper, we use the decision tree algorithm to build a model to predict the time to generate notifications for pharmacy retailers. We implement our model using the SVM operator on the RapidMiner platform and the output is a classifier model that will help to determine when future notifications will be sent. The performance metrics are shown in Tables 1–5.

- *Support vector machine model/classifier:* This algorithm is a text classification model that performs well in different domains. It was developed by Vapnik (2013) for binary classification. However, it has been applied successfully to many applications, such as Cristianini et al. (2000). In this study, the linear support vector machine algorithm is used for text classification and we made use of the SVM model in RapidMiner to build the SVM classifier. To train and test the classifier, we divided the dataset into two classes. The performance metrics are shown in Tables 1–5.

- *Naïve Bayes model/classifier:* The Naïve Bayes classifier is a popular algorithm used for text classification in several domains (Joachims, 1998). It is a simple probabilistic classifier which applies the Bayes theorem which is used to predict the class of a new document. In contrast to other classifiers, a Naïve Bayes model is efficient since it only requires a small training dataset to estimate the output

(McCallum et al., 1998). In this research, we implemented the Naïve Bayes model using the Naïve Bayes operator on the RapidMiner platform. The performance metrics are shown in Tables 1–5.

Table 1 Accuracy overall

Generalised linear model	96.9%
Logistic regression model	90.8%
Deep learning model	98.5%
Decision tree model	100.0%
SVM model	92.3%
Naïve Bayes model	92.3%
Overall accuracy = 95.1%	

Table 2 Classification error overall

Generalised linear model	3.1%
Logistic regression model	9.2%
Deep learning model	1.5%
Decision tree model	0.0%
SVM model	7.73%
Naïve Bayes model	7.7%
Overall classification error = 4.8%	

Table 3 Precision overall

Generalised linear model	96.9%
Logistic regression model	96.9%
Deep learning model	100.0%
Decision tree model	100.0%
SVM model	92.3%
Naïve Bayes model	92.3%
Overall precision = 96.4%	

Table 4 Recall overall

Generalised linear model	100.0%
Logistic regression model	93.6%
Deep learning model	98.5%
Decision tree model	100.0%
SVM model	100.0%
Naïve Bayes model	100.0%
Overall recall = 98.6%	

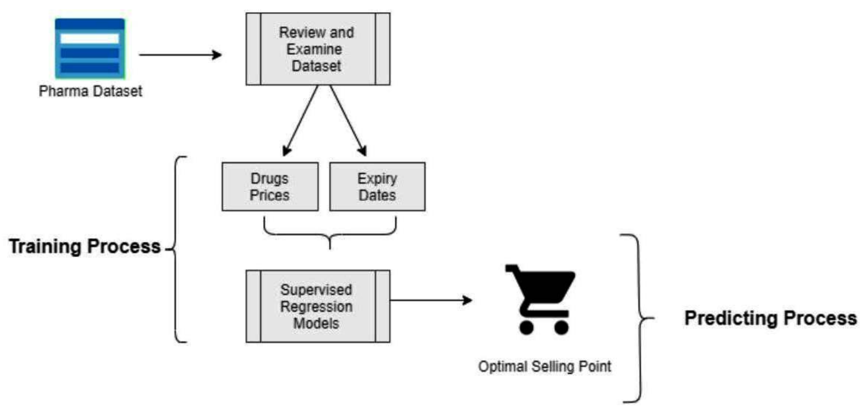
Table 5 F measure

Generalised linear model	98.4%
Logistic regression model	95.0%
Deep learning model	99.2%
Decision tree model	100.0%
SVM model	96.0%
Naïve Bayes model	96.0%
Overall F measure = 97.4%	

8 Experiment setting for the decentralised marketplace

In this section, we present our mechanism for predicting the optimal selling price using Azure machine learning and the RapidMiner platform to generate the best price for drugs which are about to expire , as shown in Figure 7.

Figure 7 The experiment framework for e-marketplace (see online version for colours)



Our model consists of three phases:

- stage 1: preparing the dataset
- stage 2: the training process
- stage 3: the predicting process.

First, the dataset comprises several columns namely, drug-name; drug-price; expiry-date and consists of about 780 records. Then, we examined the dataset manually to ensure the quality of the data. Second, we trained various supervised algorithms using the training dataset with drug-name; drug-price; and expiry-date as inputs. Third, we tested our models for the evaluation and to examine their ability to predict.

In this experiment, we split the dataset into training set comprising 70% of the data and a testing (or validation) set containing the remaining 30%. During the training process, the model learns from the training data, iteratively optimising its parameters to minimise the prediction errors. This phase involves employing various algorithms to capture underlying patterns and relationships within the data. The model's performance is then evaluated on the testing set, unseen during training, to assess its generalisation capabilities. This separation of data into training and testing subsets helps gauge how well the model can predict on unseen data, providing essential insights into its effectiveness and potential overfitting. Striking the right balance between training and testing data allocation ensures the model's ability to make accurate predictions on real-world data beyond the training dataset.

In this paper, we used two machine learning platforms – Azure ML (Machine Learning Studio, 2022) and Rapid Miner (The RapidMiner Platform, 2022). We evaluated and compared nine algorithms for predicting the accuracy of the selling price for the drugs. The algorithms that we selected were not available in one platform; rather they were available across two different platforms. Hence, we selected the two platforms to use pre-packaged algorithms for our evaluation. Subsequently, the performance of the algorithms across the two platforms was evaluated using the benchmark (root mean square error).

8.1 Optimal price predictive model using Azure machine learning

Four models have been used for predicting optimal price as follows:

- *Decision forest regression:* The decision forest regression model performs a sequence of simple tests for each tree where the output of each tree makes a prediction until a decision is reached for all trees in the model. This model is widely used in the sale of products and pricing. This model has a huge number of applications, as described in Criminisi et al. (2012). In this study, we made use of the decision forest regression in Azure machine learning by dividing our dataset into two groups, 70% and 30% for training and testing, respectively. Visualising the score and evaluating the models show us how far the predictive values vary from the original price calculated. Table 6 details the performance of this model.
- *Neural network regression:* This type of regression can analyse complex problems and provide accurate answers. Training this type of regression will perform gradient descent to find the best coefficients to better fit the data (Specht et al., 1991). Neural network regression is a supervised learning method dealing with numerical values, therefore it requires a labelled and numerical dataset. In this experiment, we used the neural network regression model to obtain the optimal regression coefficients and the optimal weight for the model. Evaluating the model values shows how closely the data fits the model, with the coefficient of determination being 0.92 and the root mean squared error being 0.48. Table 7 shows the performance of this model.
- *Boosted decision tree regression:* This regression model uses boosting which means each tree is dependent on prior trees. This type of regression learns by fitting the remaining trees that preceded it, which helps to improve the accuracy of the model. The boosted decision tree builds a series of regression trees in a step-wise manner, using a predefined loss function to measure the error in each step and correct it in the next level (Elith et al., 2008). The evaluation of this model shows an excellent coefficient of determination score of 0.97 and the mean

absolute error of around 0.26. Table 8 provides the evaluation metrics of this model.

- *Bayesian linear regression:* This type of regression uses linear regression supplemented by additional information in the form of combined prior parameter information to generate estimates for these parameters. This model does not find the single best value of the model parameters, it determines the posterior distribution for the model parameters. This algorithm is commonly used for predicting the value of the dependent variable (Baldwin and Larson, 2017). In this study, we made use of Bayesian linear regression to predict the value of the variable 'discount-price' for each drug. Analysing and evaluating machine learning after the training gives us an acceptable value of root mean squared error of 0.75. Table 9 lists the evaluation metrics for this model.

Table 6 Decision forest regression model – performance

Negative log likelihood	152.6
Mean absolute error	0.81
Root mean squared error	1.2
Relative absolute error	0.059
Relative squared error	0.047
Coefficient of determination	0.99

Table 7 Neural network regression model – performance

Mean absolute error	0.33
Root mean squared error	0.48
Relative absolute error	0.02
Relative squared error	0.007
Coefficient of determination	0.92

Table 8 Boosted decision tree model – performance

Mean absolute error	0.26
Root mean squared error	0.98
Relative absolute error	0.02
Relative squared error	0.003
Coefficient of determination	0.997

Table 9 Bayesian linear regression model – performance

Negative log likelihood	405.1
Mean absolute error	0.055
Root mean squared error	0.075
Relative absolute error	0.04
Relative squared error	0.01
Coefficient of determination	1.0

8.2 Optimal price predictive model using RapidMiner machine learning

Four models have been used for predicting optimal price as follows:

- *Generalised linear model regression:* The generalised linear model (GLM) differs from other models by its ability to test nonlinear models in the context of regression. GLM is a mathematical framework and a supervised mechanism. This model is widely used because of its natural approximation for complex functional relationships and it is straightforward in terms of estimating unknown parameters (Myers et al., 2012). In this study, we apply generalised linear regression to our dataset using the RapidMiner platform and the performance of this model is shown in Table 10. The expected output is a regression model that will predict the optimal selling point for nearly expired drugs.
- *Deep learning regression:* The deep learning model is a deep neural network that is trained to extract features from a large group of examples to assign labels to textual units. It has been proven to be powerful in mimicking human skills. It has a wide range of applications as detailed in Sameerunnisa et al. (2017). In this study, the deep learning algorithm is used for regression to build a mathematical equation to predict the optimal price to sell expired drugs in the marketplace and we designed and applied deep learning in RapidMiner to build the model. The performance metrics results of this model are shown in Table 11.
- *Decision tree regression:* The decision tree model has a root at the top and grows downwards. This algorithm splits the dataset into segments or smaller branches, and all segments form the decision tree. Decision tree regression is used to predict the target variable whose values are continuous in nature. A regression tree can easily handle complicated data. This model has been widely used for data mining, as shown in Quinlan (1986). In this paper, we use the decision tree algorithm to build a model to predict the best selling price depending on the available amount of drugs and their expiry date. We implement our model using the SVR operator on the RapidMiner platform and the output is a regression model that will determine the discount. The performance metrics are shown in Table 12.
- *Support vector regression:* Support vector regression (SVR) uses the same principle as SVM, but for regression problems. This algorithm can be a regression model which performs well in different domains. It was developed by Vapnik (2013) for both binary classification and regression. However, it has been applied successfully to many applications, as discussed in Cristianini et al. (2000). In this study, the linear support vector regression algorithm is used for regression and we made use of the SVR model in RapidMiner to build our model. To train and test the SVR model, we divided the dataset into two classes, 70% and 30%, for training and testing respectively. The performance metrics are shown in Table 13.

Table 10 Generalised linear regression model – performance

Root mean squared error	0.188 +/– 0.032 (micro average: 0.191 +/– 0.000)
Absolute error	0.149 +/– 0.034 (micro average: 0.149 +/– 0.119)
Relative error lenient	1.14% +/– 0.60% (micro average: 1.15% +/– 2.84%)
Squared error	0.036 +/– 0.012 (micro average: 0.036 +/– 0.054)
Correlation	1.000 +/– 0.000 (micro average: 1.000)

Table 11 Deep learning model – performance

Root mean squared error	0.489 +/– 0.082 (micro average: 0.495 +/– 0.000)
Absolute error	0.373 +/– 0.042 (micro average: 0.374 +/– 0.324)
Relative error lenient	2.95% +/– 2.19% (micro average: 2.97% +/– 7.29%)
Squared error	0.245 +/– 0.081 (micro average: 0.245 +/– 0.469)
Correlation	1.000 +/– 0.000 (micro average: 1.000)

Table 12 Decision tree model – performance

Root mean squared error	0.380 +/– 0.072 (micro average: 0.382 +/– 0.000)
Absolute error	0.294 +/– 0.039 (micro average: 0.298 +/– 0.320)
Relative error lenient	1.71% +/– 1.06% (micro average: 1.69% +/– 6.30%)
Squared error	0.221 +/– 0.073 (micro average: 0.221 +/– 0.432)
Correlation	1.000 +/– 0.000 (micro average: 1.000)

Table 13 Support vector model – performance

Root mean squared error	0.023 +/– 0.010 (micro average: 0.025 +/– 0.000)
Absolute error	0.016 +/– 0.005 (micro average: 0.016 +/– 0.019)
Relative error lenient	0.31% +/– 0.53% (micro average: 0.32% +/– 1.66%)
Squared error	0.001 +/– 0.001 (micro average: 0.001 +/– 0.002)
Correlation	1.000 +/– 0.000 (micro average: 1.000)

9 Results and discussion

In this section, we discuss the results of our framework implementation for both the EWS and the decentralised marketplace.

9.1 Early warning system

We developed an on the fly date-based early warning system following to the experiment framework in Figure 6. The work on how each notification can be added to the PharmaWeb Server and generate a transaction on PharmaBlock platform is illustrated in Section 5. A summary of the date-based EWS experiments is given in sections 4 and 5 with an overview of several machine learning models applied to our framework with their performance. Additionally, to conduct supervised machine learning, we built our dataset using the RapidMiner platform. We conducted 2-fold cross-validation in this experiment, meaning the data is divided into two groups, one being the training set and the other being the test set. We used six approaches to predict the date to generate the notification based on the drug expiry date on our PharmaWeb server. To evaluate the classification of our model, we used multiple evaluation metrics, namely accuracy, classification error, precision, recall and F measure for each approach. Tables 1–5 provide details on the performance of each approach. Recall and precision refer to the recall ratio and precision ratio of the relevant generated warnings, respectively. Accuracy is the most popular metric used to assess classifier efficiency. Overall, accuracy describes the total number of prediction alarms that are correctly generated as a percentage compared to the total number of alarm values (Müller et al., 2016). Table 1 shows the overall accuracy of the different approaches. We also used the F measure metric to measure the accuracy of our model when it is applied to different approaches. The classification error in this study indicates the overall misclassification of the dataset, meaning the number of alarms that are not generated on time or not generated at all. We conducted the experiment and the results show that the decision tree model scores the best performance over the other classification models, whereas the logistic regression model has the worst performance.

9.2 Decentralised marketplace

We developed an on the fly intelligent and predictive analytical approach to predict an optimal price to sell products in a decentralised marketplace, as shown in Figure 5. The work develops intelligent decision making centred on the just-in-time sale of drugs at an optimal price to consumers on a decentralised marketplace platform. A summary of the predictive analytical approaches is given in Sections 4 and 5 with an overview of several machine learning algorithms applied to our framework with their performance. Additionally, to conduct supervised machine learning, we built our dataset using the RapidMiner platform and the Azure machine learning platform. We conducted a 2-fold cross-validation in this experiment, meaning the data is divided into two groups, one being the training set and the other being the test set. We used eight approaches to predict the optimal price for selling medicines on our PharmaBlock platform. To evaluate our model, we used well-known evaluation metrics, namely mean absolute error, root mean squared error, relative absolute error, relative squared error and the coefficient of determination for each approach. Tables 6–13 detail the performance of each approach. RMSE and MAE are regularly employed in model evaluations and are two of the most commonly used metrics to assess regression efficiency (Chai and Draxler, 2014). RMSE indicates how concentrated the data is around the regression line of best fit and a smaller RMSE indicates smaller forecast errors, meaning that our model scores the best values of between 0.023 and 1.2 for all the algorithms. The results of our experiments show that the support vector regression model achieves the best performance when using the RMSE metric compared to the other regression models, whereas the decision forest regression model has the worst performance.

10 Conclusions and future work

The main goal of this study was to improve the strategies and increase the visibility of medicines in the pharmaceutical supply chain, reducing the number of counterfeit medications on the market and the wastage of expired drugs.

To achieve this goal in this paper, firstly we presented an early warning system and the purpose of the EWS was to proactively determine drugs which were near expiry date. The results of this analysis show that more than 90% of the notifications sent by the EWS to inform pharmacy retails about nearly expiring drugs were generated correctly and they were notified via the blockchain platform. Furthermore, once the near to expiry drugs have been determined, in this paper we proposed the framework which can be used by the steak-holders to sell those drugs in the e-marketplace.

In future work, we will develop an artificial intelligence predictive model on top of PharmaBlock to predict the future demand for drugs.

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