The Internet of Things (IoT) has grown more pervasive in recent years. It makes it possible to describe the physical world in detail and interact with it in several different ways. Consequently, IoT has the potential to be involved in many different applications, including healthcare, supply chain, logistics, and the automotive sector. IoT-based smart healthcare systems have significantly increased the value of organizations that rely heavily on IoT infrastructures and solutions. In fact, with the recent COVID-19 pandemic, IoT played an important role in combating diseases. However, IoT devices are tiny, with limited capabilities. Therefore, IoT systems lack encryption, insufficient privacy protection, and subject to many attacks. Accordingly, IoT healthcare systems are extremely vulnerable to several security flaws that might result in more accurate, quick, and precise diagnoses. On the other hand, blockchain technology has been proven to be effective in many critical applications. Blockchain technology combined with IoT can greatly improve the healthcare industry's efficiency, security, and transparency while opening new commercial choices. This paper is an extension of the current effort in the IoT smart healthcare systems. It has three main contributions, as follows: (1) it proposes a smart unsupervised medical clinic without medical staff interventions. It tries to provide safe and fast services confronting the pandemic without exposing medical staff to danger. (2) It proposes a deep learning algorithm for COVID-19 detection-based X-ray images; it utilizes the transfer learning (ResNet152) model. (3) The paper also presents a novel blockchain-based pharmaceutical system. The proposed algorithms and systems have proven to be effective and secure enough to be used in the healthcare environment.

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# Developing Trusted IoT Healthcare Information-Based AI and Blockchain

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**Abstract:** The Internet of Things (IoT) has grown more pervasive in recent years. It makes it possible to describe the physical world in detail and interact with it in several different ways. Consequently, IoT has the potential to be involved in many different applications, including healthcare, supply chain, logistics, and the automotive sector. IoT-based smart healthcare systems have significantly increased the value of organizations that rely heavily on IoT infrastructures and solutions. In fact, with the recent COVID-19 pandemic, IoT played an important role in combating diseases. However, IoT devices are tiny, with limited capabilities. Therefore, IoT systems lack encryption, insufficient privacy protection, and subject to many attacks. Accordingly, IoT healthcare systems are extremely vulnerable to several security flaws that might result in more accurate, quick, and precise diagnoses. On the other hand, blockchain technology has been proven to be effective in many critical applications. Blockchain technology combined with IoT can greatly improve the healthcare industry's efficiency, security, and transparency while opening new commercial choices. This paper is an extension of the current effort in the IoT smart healthcare systems. It has three main contributions, as follows: (1) it proposes a smart unsupervised medical clinic without medical staff interventions. It tries to provide safe and fast services confronting the pandemic without exposing medical staff to danger. (2) It proposes a deep learning algorithm for COVID-19 detection-based X-ray images; it utilizes the transfer learning (ResNet152) model. (3) The paper also presents a novel blockchain-based pharmaceutical system. The proposed algorithms and systems have proven to be effective and secure enough to be used in the healthcare environment.

**Keywords:** Internet of Things (IoT); blockchain; smart healthcare systems; transfer learning; deep learning



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## 1. Introduction

The world has recently faced many difficult challenges in the health sector since the spread of COVID-19 and the mutants of the virus. This poses significant challenges to health systems worldwide in terms of balancing the needs of providing additional services required to manage the pandemic while maintaining and improving access to essential health services [1].

Health and care workers (HCWs) play a critical role in the worldwide pandemic response. The pandemic has increased the hazards of work exposure to a new, rapidly spreading illness, while also mandating changes in duties and responsibilities for a wide range of professional tasks and situations [2]. There is little doubt that the health and care industry is one of the most affected by the pandemic since employees face several hazards that harm their physical, mental and social health. Healthcare workers are more likely than the general population to get infected with the COVID-19 virus [3].

Many HCWs and their families were infected and died because of the pandemic, and the consequences are currently being measured using a diverse set of anecdotal evidence and variable quality criteria [2].

The pandemic is also affecting the availability of health staff and their capacity to provide critical services and meet expanding demand. During the COVID-19 pandemic, health personnel may encounter issues such as a lack of sufficient Personal Protective Equipment (PPE) and other necessary equipment; infection, quarantine, social prejudice, assaults, and the dual task of caring for friends and family members [3]. As a result, a radical solution to safeguard healthcare professionals and their families is necessary; this research study proposes a smart health system that does not rely on medical personnel's presence. COVID-19 is chosen as a case study.

Several algorithms for determining COVID-19-related mortality among HCWs can be classified as follows [3]:

- The first approach, the crude mortality rate from each country, or the total number of fatalities reported to the World Health Organization (WHO) COVID-19 Dashboard divided by population size was applied to simply estimate the number of deaths among HCWs. This evaluation implies that HCWs, regardless of age or gender, have a similar infection risk and risk of mortality to the general population, but a greater risk of infection (both at the workplace and the community, particularly in countries lacking practices, provisions, and guidance on infection prevention and control). Another issue is its poor estimate. Only 6643 of the 3.45 million COVID-19-related deaths reported to WHO were HCWs as shown in Figure 1a.
- The second approach is improving on the first approach by using age- and sex-indirect standardization and age- and sex-specific mortality estimates. The reported COVID-19 fatalities were reallocated within each country based on the age and gender distribution of mortality reported to WHO for chosen countries. The International Labor Organization's (ILO) estimated number of HCWs (split by gender) was redistributed based on the age and gender mix of the population size in the age range of 25–64 years. According to population estimates, roughly 115,500 HCWs (ranging from 80,000 to 1,600,001) of the 135-million-person global health and care workforce may have died. The age- and gender-specific death rates for each nation were then estimated and applied to the country's redistributed HCW population. If the anticipated overall mortality in high-burden nations is included, the top range of estimates might exceed 180,000. This strategy disregards any of the potentially increased risks indicated above if HCWs have an exposure risk equivalent to the general population as presented in Figure 1b.
- The third approach is based on the analysis of SARS-CoV-2 infections and deaths among HCWs, which discovered that infections of HCWs accounted for 12.5% (confidence interval 6.2%, 23.5%) of all SARS-CoV-2 infections between March and July 2020. The decreasing proportion of HCW infections among all SARS-CoV-2 illnesses reported to WHO supports the lower bound of 6.2% of all cases (from 5.7% in May 2020 to 1.8% by May 2021). The meta-analysis revealed the prevalence of death among HCWs, which was then multiplied by the estimated infection rate among HCWs, yielding an estimate of 6.2% of all SARS-CoV-2 infections reported by each nation as illustrated in Figure 1c.
- In the fourth approach, a separate estimate based on meta-analysis summary statistics yields a global estimated total of 79,700 HCW fatalities (as shown in Figure 1d), which supports the 83,000 number (with figures falling between 39,900 and 159,500). It may be

argued, however, that the lowest estimate in the range—39,900 HCWs—is the least plausible because it combines the lowest infection rate (6.2%) and mortality rate (6.2%) (0.4%).

The number of deaths among HCWs from COVID-19 appears to be substantially higher than officially recorded.

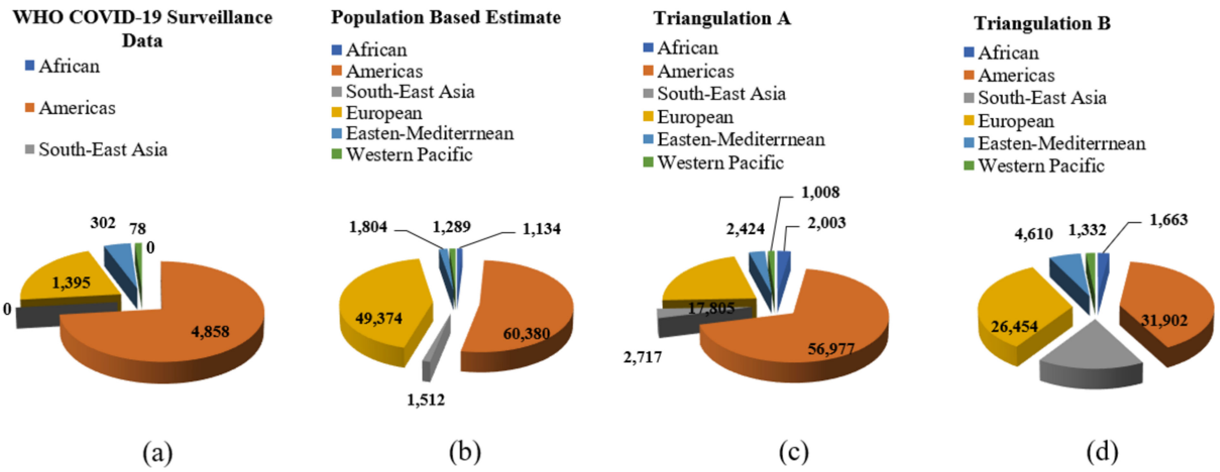


**Figure 1.** Estimates of the number of deaths in HCWs due to COVID-19 (January 2020–May 2021) using various methods. (**a**) HCWs deaths reported to the WHO COVID-19 Surveillance, (**b**) Population-based estimate of HCW deaths, (**c**) HCWs deaths using indirect standardization, (**d**) HCWs deaths using results of meta-analysis (based on PCR testing).

The Institute for Health Metrics and Evaluation (IHME) announced the findings of their analysis employing excess all-cause mortality methodologies about the same time that WHO completed its research [3]. Table 1 compares population-based estimates of COVID-19-related HCW fatalities in the top 20 countries (which account for 80% of worldwide COVID-19 deaths reported to WHO), using the IHME's estimate of all COVID-19-related deaths as the denominator. Surprisingly, considering the high-burden nations studied by IHME, HCW mortality is expected to reach 179,500. After these analyses and statistics, it became clear that there was a need for a method to protect medical staff and their families for their vital and pivotal role in successive crises in the health sector, dealing with epidemics, and providing health care for ordinary patients, in addition to the burdens caused by the virus crisis and recent epidemics. As a result, in this work, we propose a smart clinic without medical personnel to identify and diagnose infected patients and possible viral carriers based on diagnosing the case in more than one stage utilizing temperature sensors, oxygen levels in the blood, and X-rays.

The remainder of the paper is structured as follows: Section 2 presents an introduction to the Internet of Things (IoT) and the blockchain. The proposed smart clinic is presented in Section 3. Section 4 illustrates the proposed COVID-19 detection from an X-ray image using deep learning. Results are presented in detail in Section 5. Section 6 presents the proposed blockchain-based pharmaceutical system. Section 7 shows the result discussion. The papers ends with a conclusion, acknowledgment, and references.

**Table 1.** Comparison of the population-based deaths in HCWs related to COVID-19 using surveillance data reported to WHO and IHME's total deaths—top-ranking countries with Polymerase Chain Reaction (PCR Test) (January 2020–May 2021) [3].

| Country | WHO Rank | IHME Rank | WHO COVID-19 Surveillance | | | Population-Based Estimated HCW Deaths | Triangulation A Indirect Standardization (by Sex and Age) | | | Triangulation B Meta-Analysis Based on PCR Testing (at 6.2% Infection) | | Based on IHME Estimated Overall Deaths |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | All Deaths | Share of All Deaths (%) | HCW Deaths | HCW Deaths | HCW Deaths (All) | HCW Deaths (Males) | HCW Deaths (Females) | HCW Deaths (at 0.8%) | HCW Deaths (at 1.6%) | HCW Deaths |
| United States of America | 1 | 1 | 578,984 | 17.3 | 59 | 39,925 | 37,633 | 21,950 | 15,683 | 16,137 | 32,274 | 62,426 |
| Brazil | 2 | 4 | 430,417 | 12.8 | 684 | 9769 | 8966 | 5430 | 3536 | 7655 | 15,311 | 13,525 |
| India | 3 | 2 | 266,207 | 7.9 | 0 | 1129 | 2053 | 1378 | 675 | 12,089 | 24,178 | 2775 |
| Mexico | 4 | 3 | 219,901 | 6.6 | 3214 | 2717 | 2870 | 1899 | 971 | 1178 | 2356 | 7625 |
| The United Kingdom of Great Britain and Northern Ireland | 5 | 6 | 127,668 | 3.8 | 0 | 8562 | 3177 | 1586 | 1519 | 2206 | 4411 | 14,061 |
| Italy | 6 | 7 | 123,927 | 3.7 | 269 | 3970 | 1462 | 810 | 652 | 2057 | 4114 | 5633 |
| Russian Federation | 7 | 5 | 115,480 | 3.4 | 0 | 4386 | 1532 | 803 | 729 | 2446 | 4892 | 22,546 |
| France | 8 | 14 | 106,666 | 3.2 | 4 | 6708 | 2545 | 1282 | 1263 | 2854 | 5708 | 8344 |
| Germany | 9 | 16 | 86,025 | 2.6 | 0 | 5809 | 2112 | 1056 | 1056 | 1778 | 3556 | 8152 |
| Colombia | 10 | | 79,760 | 2.4 | 0 | 1609 | 1506 | 891 | 615 | 1522 | 3043 | |
| Spain | 11 | 15 | 79,095 | 2.4 | 148 | 2845 | 998 | 503 | 495 | 1778 | 3556 | 4453 |
| Islamic Republic of Iran | 12 | 8 | 76,433 | 2.3 | 0 | 737 | 877 | 639 | 238 | 1355 | 2710 | 1679 |
| Poland | 13 | 11 | 71,609 | 2.1 | 5 | 2013 | 676 | 318 | 358 | 1415 | 2829 | 4213 |
| Argentina | 14 | | 69,254 | 2.1 | 534 | 1814 | 1883 | 1209 | 674 | 1608 | 3216 | |
| Peru | 15 | 12 | 65,316 | 1.9 | 0 | 896 | 877 | 550 | 327 | 929 | 1858 | 2027 |
| South Africa | 16 | 10 | 55,124 | 1.6 | 0 | 966 | 1620 | 905 | 715 | 798 | 1596 | 2812 |
| Ukraine | 17 | 13 | 47,942 | 1.4 | 615 | 1342 | 448 | 229 | 219 | 1067 | 2133 | 3877 |
| Indonesia | 18 | 17 | 47,823 | 1.4 | 0 | 314 | 534 | 321 | 213 | 860 | 1720 | 760 |
| Turkey | 19 | | 44,301 | 1.3 | 0 | 803 | 318 | 178 | 140 | 2527 | 5055 | |

**Table 1.** *Cont.*

| Country | WHO Rank | IHME Rank | WHO COVID-19 Surveillance | | | Population-Based Estimated HCW Deaths | Triangulation A Indirect Standardization (by Sex and Age) | | | Triangulation B Meta-Analysis Based on PCR Testing (at 6.2% Infection) | | Based on IHME Estimated Overall Deaths |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | All Deaths | Share of All Deaths (%) | HCW Deaths | HCW Deaths | HCW Deaths (All) | HCW Deaths (Males) | HCW Deaths (Females) | HCW Deaths (at 0.8%) | HCW Deaths (at 1.6%) | HCW Deaths |
| Czech Republic | 20 | | 29,712 | 0.9 | 87 | 1103 | 367 | 177 | 190 | 816 | 1632 | |
| Romania | 21 | 19 | 29,413 | 0.9 | 12 | 652 | 214 | 100 | 114 | 531 | 1062 | 1943 |
| Egypt | 34 | 9 | 14,206 | 0.4 | 181 | 129 | 177 | 121 | 56 | 121 | 241 | 1544 |
| Japan | 39 | 18 | 11,365 | 0.3 | 0 | 942 | 745 | 389 | 356 | 333 | 666 | 8978 |
| Kazakhstan | 59 | 20 | 4760 | 0.1 | 0 | 119 | 46 | 24 | 22 | 203 | 406 | 2042 |
| Sub-total | | | | | | 99,259 | 73,636 | 42,748 | 30,888 | 64,263 | 128,523 | 179,415 |

## 2. Relevant Literature

This section presents a brief introduction to the Internet of Things (IoT) and the blockchain. This section presents the importance of the IoT and the blockchain when especially related to the healthcare sector. This section also presents the previous work related to IoT and blockchain in the healthcare sector.

### 2.1. Internet of Things (IoT)

The Internet of Things (IoT) has roots in practically every aspect of society, including numerous businesses such as the automobile industry, energy sector, industrial sector, and healthcare sector [4]. Large volumes of data are frequently created, collected, and transmitted throughout the healthcare system, which is an information-intensive medical area. Due to the sensitive nature of data and constraints such as security and privacy, storing and disseminating such a large amount of data is both necessary and difficult.

Processing and storage of smart medical devices necessitate extra procedures. Currently, storing and maintaining medical information is simplified by outsourcing confidential medical information and Electronic Health Records (EHRs) to cloud storage [5]. Because it promotes information exchange, knowledge management, and predictive analytics across the healthcare ecosystem, the cloud-based medical system improves accuracy and decreases costs compared to traditional healthcare systems [6,7]. Cloud computing, on the other hand, has several drawbacks, including security, integrity, data loss, and so on. A central administrator manages the cloud computing environment, and the central administrator may share the user's healthcare data with other third parties for commercial gain [8,9]. As a result, patients' or users' medical information must be kept and handled in a safe manner. Blockchain technology is one of the ideal alternatives for resolving this problem since it provides a reliable distributed ledger [10].

The EHR industry is now highly valued, with estimates ranging in the tens of billions of dollars [11]. However, because there are several dangers connected to privacy, security, and interoperability, exchanging health data requires a safe and trustworthy infrastructure. First, health data is extremely sensitive to privacy, especially since more and more data is being kept in the cloud. As a result, the risks of sensitive data disclosure and leakage are growing. Second, centralized architectures are commonly employed in modern systems as well as security procedures. As a result, properly integrating interoperability among healthcare systems that are deployed in many locations is difficult. Furthermore, consumers have limited access to private health data, which is a serious challenge [12]. Considering the notion of self-ownership, as well as the rising usage of mobile platforms and portable computing devices, it is unavoidable to design a newer version of EHR systems that ensures user access control and security preservation in a more distributive but effective manner [13].

Such systems must have the capacity to communicate data safely and efficiently [14–16]. They must also enable more access control, privacy, and anonymity to the persons concerned. Individuals will become hesitant to share crucial information or postpone seeking treatment if security, privacy, and trust are not handled properly [17]. Many health data systems now rely on a single entity to maintain private health data, which is extremely vulnerable to single point of failure. Due to its distributive nature, blockchain technology has the potential to replace this dependency. It provides the capacity to distribute and immutably overcome failure and assaults [13].

It also serves as a record of the ownership of data and its authenticity [13,18]. It refers to the usage of pseudo-anonymity in conjunction with public key infrastructure (PKI) while maintaining user privacy [17]. The usage of blockchain technology in healthcare was discussed [19]. The research supports the use of blockchain technology in the healthcare domain, including privacy preservation for prediction modeling, increased large-scale interoperability among institutions, invariability of health history records, improved health assurance process, interchange of health data, artificial intelligence supporting healthcare models, identity management, revenue strategies, and data record [19,20].

### 2.2. Introduction to the Blockchain

The blockchain network allows users to share resources without worrying about a single point of failure [21]. As a result, bottlenecks at the central location are eliminated. A blockchain transaction contains user data and links to a ledger in the form of a block. A block preserves the history of previous transactions indefinitely, while new transactions are logged in the current one. The way in which a new block is added to a blockchain is determined by consensus procedures in a blockchain network [10].

In the last several years, blockchain technology has been thoroughly investigated. The notion of blockchain was developed as the supporting mechanism of the digital cryptocurrency Bitcoin [22]. The basic concept of blockchain technology provides a foundation for cooperation between unknown and untrustworthy things, as well as corroborating the widely disseminated features of mobile (smart health) devices, without the need for a central security and authentication authority, as in current cloud computing architectures [23]. This fundamental technology is based on an immutable "public ledger", which is a shared database of data among all members. This public ledger comprises data blocks that are connected using a cryptographic hash key. Proof of Work (PoW) is the term for the connecting process [18]. The ledger and the consensus method are both resistant to data tampering by design. Block data cannot be changed after the fact since this invalidates earlier block hashes in the blockchain and disrupts node consensus. The use of blockchain technology allows Bitcoin's public distributed ledgers to perform digital money transactions cheaply and securely without the need for a third party to validate the transaction, avoiding the recurrent "double spending" problem [23]. When a transaction is launched, a smart contract is run as a stored procedure. Decentralized control, data transparency and auditability, distributed information, and security against hostile actors are all fundamental features of blockchain technology [18,23].

The blockchain is a distributed database of records that are obtained via digital transactions carried out by various network participants [18]. Each network transaction is authenticated by the majority of the network system members. Each transaction record is saved in this concept. Bitcoin is one of the most uncorrupted blockchain applications. The reason for this is that it uses a digital ledger that is spread over the network to record all transactions. When a new piece of data is saved in a block, it is added to the chain of blocks. Blockchain, as the name implies, is a collection of interconnected blocks [18]. The following four steps must be completed to add a single block to the blockchain. The first is that there must be a transaction. Consider the case of a last-minute Amazon purchase. We come to locate the last item and buy it after frantically browsing through several of the items [13].

The second need is that the transaction is validated. The transaction that we performed after purchasing the goods must be validated. In the same way as other public records, such as Wikipedia, will have a quality control system in place for new data entries, there will be a quality control system in place for new data entries. However, in the case of blockchain, it is a computer network with thousands of machines dispersed throughout the globe. When a purchase is made, this network of computers is compelled to check whether the transaction has occurred, that is, they examine the transaction data such as the time, amount, and so on. The third is that the validated transaction will be saved in a block. It will be assigned a green signal when the transaction has been verified. The block will retain all transaction data, including the money, the customer's signature, and Amazon's signature. This block will be joined by thousands of others [13].

Finally, a hash value must be assigned to the newly inserted block. The block is assigned a unique and identifiable hash value when the transaction is validated. The block will be added to the blockchain after the hash value has been assigned to it. The block becomes available to everyone, including the user once it is inserted. When, where, and by whom the block is uploaded to the blockchain may all be seen by the user [13].

A blockchain is a collection of complete and valid transaction records in the form of a chronological succession of blocks. A reference (hash value) connects each block to the one before it, producing a chain. The parent block of a given block is known as the genesis block, while the first block is known as the parent block.

As illustrated in Figure 2, a block comprises the block header and the block body [22].

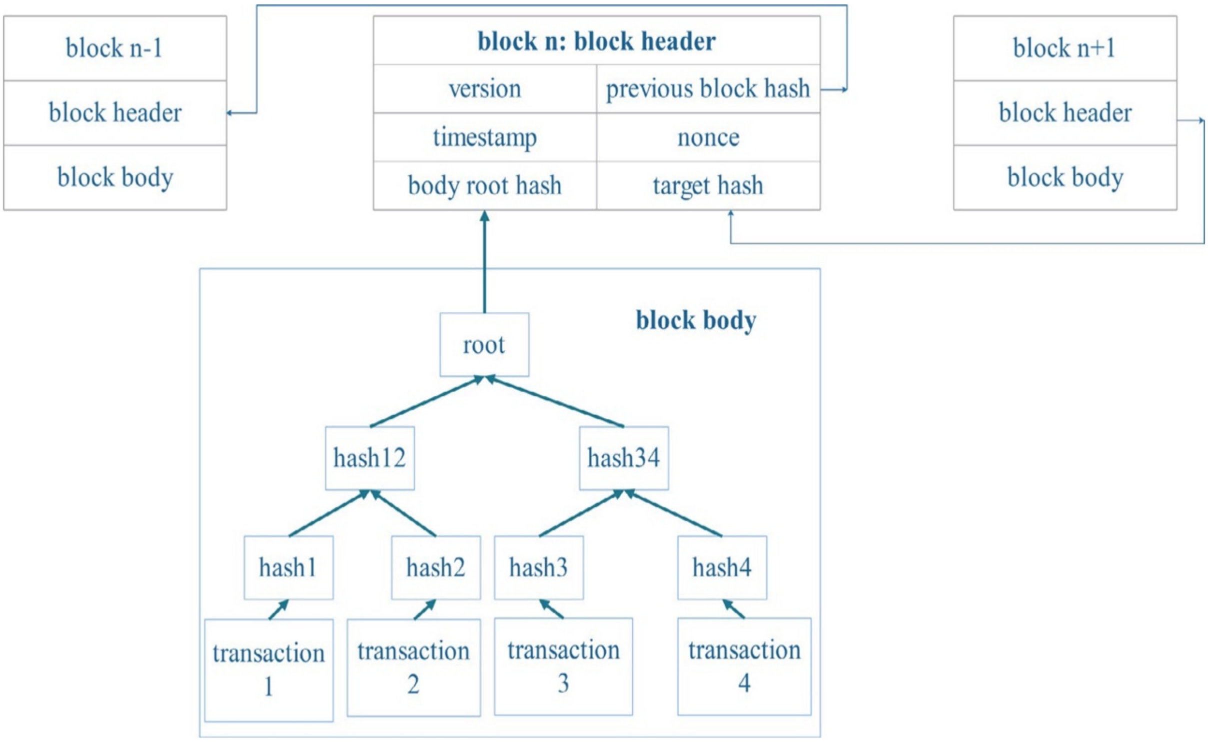


**Figure 2.** Block structure [22].

The block header provides the following information [22]:

- Block version: block validation rules.
- Previous block hash: the previous block's hash value.
- Timestamp: the current block's creation time.
- Nonce: a 4-byte random field that miners adjust for every hash calculation to solve a PoW mining puzzle.
- Body root hash: the hash value of the Merkle tree root built by transactions in the block body.
- Target hash: target threshold of the hash value of a new valid block. The target hash is used to determine the difficulty of the PoW puzzle.

The block body is made up of verified transactions from a given time. The Merkle tree, in which every leaf node represents a transaction, and every non-leaf node is the hash value of its two concatenated child nodes, is used to record all legitimate transactions. Because every node may certify the validity of any transaction by the hash value of the corresponding branches rather than the complete Merkle tree, such a tree structure is efficient for verifying the transaction's existence and integrity. Meanwhile, any changes to the transaction will cause a new hash value to be generated in the top layer, resulting in a faked root hash [24]. Furthermore, the maximum number of transactions that may be contained in a block is determined by the size of each transaction as well as the block size. These blocks are then linked together in an append-only structure using a cryptographic hash function. Because it is difficult to change or delete the already validated data, new data is only added in the form of extra blocks linked with prior blocks. As previously stated, every change to one of the blocks will result in a new hash value and link relationship. As a result, immutability and security are achieved [25].

There are three different forms of blockchain technology [26,27]:

1. Public: A public blockchain, also known as the permissionless blockchain, is one that does not require any permissions. By performing a bitcoin transaction, mining a block, or operating and connecting as a node, anybody may become a participant in this blockchain.
2. Permission blockchain: The private blockchain is also known as the permission blockchain. Only members of the organization or chosen persons can participate in the event, which is closed to the public.
3. Consortium: This is a somewhat centralized and decentralized system. This type of blockchain is managed by a consortium of companies, whereas others are managed by a single company.

Blockchain has several advantages [27]:

1. Time Preservation: Because the certification of the central authority is required for settlements, this procedure is quicker and less expensive.
2. Cost Reduction: It does away with third-party verification and direct asset transfer. Sharing a copy of the ledger created by each participant eliminates middlemen and decreases transaction effort. This is how the blockchain helps you save money.
3. Increased Security: The client system serves as a deterrent to cybercrime and fraud. It is impossible to tamper with the data on the blockchain since it is shared with millions of people.

There are several benefits to the blockchain technology in healthcare to ensure trust among healthcare participants.

1. Administration of patient consent

The reliability of electronic health records (EHRs) that contain a patient's medical history, diagnoses, medications, and treatment protocols is essential to the efficacy of virtual care and health monitoring [28]. To keep a patient's medical records current, the EHRs containing extremely sensitive and confidential information must be securely shared with peers such as hospitals, pharmacies, and health regulatory agencies. By establishing data access and utilization regulations, telemedicine health legislation has provided individuals with greater ownership and management opportunities over their clinical data. Due to the absence of intermediaries, blockchain technology can aid in enforcing trust. Consent management is guaranteed and protected by blockchain via several peers that are members of various participating organizations [29,30].

2. Remote treatment traceability

For a remote patient's health to be accurately assessed during the practice of telehealth and telemedicine, patients and specialists must interact electronically and face-to-face. Direct-to-consumer (D2C) and business-to-business (B2B) models are used in the delivery of telehealth services. Patients in the former model can electronically communicate with doctors to discuss their health conditions, whereas caregivers in the latter model can remotely participate in consultation and medical education services (e.g., patient surgery) via tools that support audio and video conferencing. Health organizations are unable to manage the silos of patient health records in existing telemedicine systems due to limited data sharing among themselves [31]. Blockchain technology provides all stakeholders with a unified and consistent view of patient EHRs [30]. Participating organizations can trace a patient's medical history and recommend the appropriate treatment. Using blockchain technology, audits can be performed to determine who accessed electronic records and what transactions were carried out [31,32].

3. Traceability of medical kits and devices used at home

In-home medical kits and devices can help patients self-diagnose in a non-clinical setting. The use of commercially available test kits and devices to assess specific biochemical responses for self-checkup and early disease detection can reduce overall healthcare costs. The lack of transparency, visibility, and data provenance about medical kits in traditional centralized telehealth-based systems makes it difficult for physicians and patients to obtain reliable medical kits from reputable manufacturers. In such a case, blockchain technology can be used to record transactions related to the ownership and performance of testing kits on the distributed ledger immutably and transparently [32].

4. Personal health records must be kept secure

A Personal Health Record (PHR) is a collection of an individual's health data, personal information, and other information related to the patient's care. The PHR records are created, maintained, and managed by the data owner. Traditional systems for providing virtual healthcare services are mostly based on cloud platforms, which are less reliable because they are managed by a single entity. PHR integrity is also jeopardized in traditional cloud-based systems. The inherent features of decentralized blockchain technology allow the owner of medical data to keep the data private [29,31,33].

5. Automated payments

The blockchain supports micropayments in the telehealth sector by accepting cryptocurrency tokens as payment [34]. As a result, the direct transfer of cryptocurrency tokens to the service provider's wallet provides a fast, secure, transparent, and auditable system that does not require a central mediation service to resolve payment settlement disputes [28,34].

6. Reliable monitoring of elderly care services

The Internet of Things (IoT) technological advancements can help the telehealth sector remotely monitor a patient's health using precise biomedical sensors [26]. The biomedical sensors can continuously monitor and store health data on a high-performance edge server, which aids in the analysis of a patient's health condition. Vital indicators such as blood pressure and body temperature can be linked to health data. However, inaccurate data captured by a faulty device can result in medical errors. To address this issue satisfactorily, the decentralized blockchain technology uses smart contracts to register and verify the access rights of biomedical sensors to store the EHR on the ledger [31]. Smart contracts can send timely alerts to doctors and health centers in the event of an emergency. In the case of in-home care, IoT-assisted blockchain systems can proactively send a medication refill notification to the patient [35].

7. Drug delivery and pharmacy refill traceability

Blockchain technology, through hash functions, can help to eliminate potential prescription errors and record alteration [28,36]. Registered pharmacists can access the drug prescriptions stored on the blockchain to verify, prepare, and deliver the medications to patients. In exchange, the shipper can record the shipment's current location on the blockchain, allowing pharmacists and patients to track and trace it. Furthermore, due to the transparency and traceability of blockchain transactions, patients and doctors can verify the legitimacy of the medicine via its data provenance [31].

8. Reliable health insurance services

Blockchain technology can help insurance providers reduce insurance fraud (consent-based). Patients can be compensated for allowing insurance companies to use their medical records [28,33,34]. Furthermore, many insurance companies provide premium holders with incentives in the form of cryptocurrency tokens for maintaining a healthy lifestyle, such as tracking gym visits. The smart devices attached to the patient can transact on the blockchain to establish trust.

9. Specialist referral services with a good reputation

In a blockchain-based solution, the referring healthcare provider can store the referral documents on an IPFS server, which returns an IPFS hash of the document for storage on the blockchain, allowing consulting healthcare specialists to access them [31]. It is possible to determine whether the stored document on the IPFS server has been altered using the

IPFS hash stored on the blockchain. The consulting healthcare specialist can examine the patient's health report, and then health specialists can store such a diagnosis report on the blockchain ledger. The referring healthcare provider can update the reputation score on the blockchain based on the total service time and satisfaction score of the consulting health specialist [31].

10. Patient follow-up care service automation

Blockchain technology can automate the patient's follow-up service. Smart contracts can automatically send a notification to the patient, physician, and nursing staff to remind them of the upcoming follow-up schedule. The physician can access the patient's transparent and immutable EHR to confirm the health status that was recorded during the last follow-up meeting (virtual). Furthermore, the patient can use a smart contract to register and share the IPFS hash with the physician for accessing health reports by using IPFS servers that can host medical test reports [28,31,33].

## 3. The Proposed Smart Clinic

This section presents the proposed smart medical clinics which depend on the medical diagnosis of the patient without medical staff. The proposed medical clinic can only serve one patient at a time. Then, the process is carried out to receive a new patient.

The proposed algorithm is divided into two phases. The first phase is entering the clinic's website which consists of three steps: the first step is registration, data collection, and receiving symptoms of the patient. The second step is generating the QR code and determining the appropriate appointment for the patient. The final step is suggesting an appropriate treatment protocol. The second phase is visiting the clinic which consists of two essential steps, the sensing and measurements stage, then the X-ray stage. The block diagram of the phases of the smart clinic is presented in Figure 3.

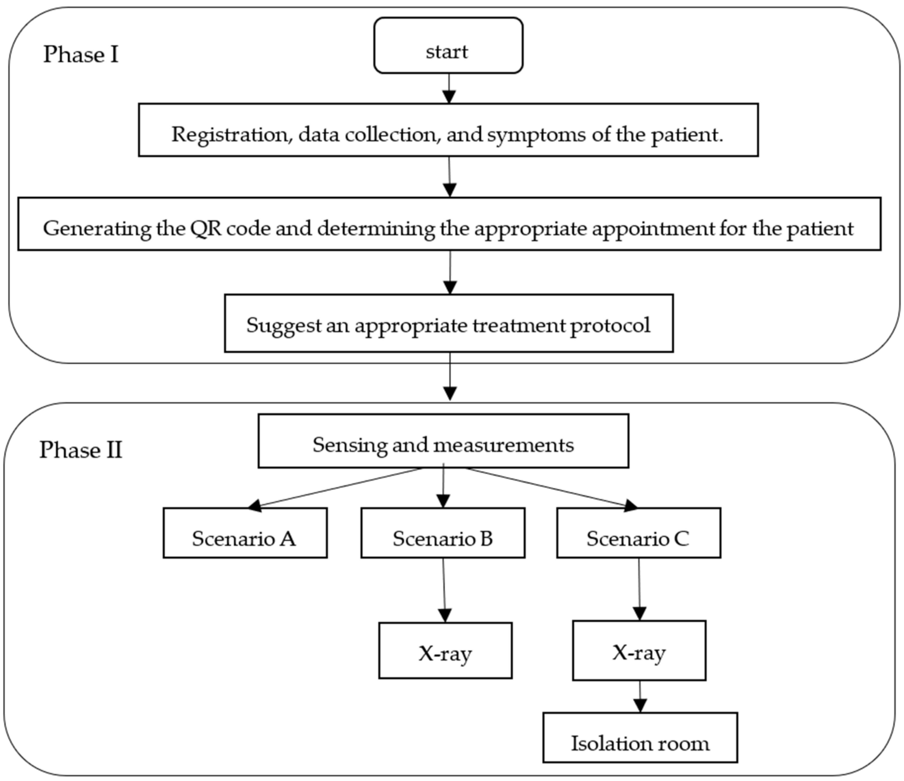


**Figure 3.** The block diagram of phases of the smart clinic.

*3.1. Phase I: The Clinic's Website*

The website is considered an interface that is used to communicate between the patient and the doctor without any physical connection between them. Because the cases of COVID-19 are exponentially increasing, a number of healthcare providers and hospitals cannot provide their services to this huge number of people at the same time, so one of the important reasons for creating the website is to organize the booking appointments for the patients. In addition, booking an appointment with only one doctor helps many patients, since the doctor gives advice to them remotely. Figure 4 presents the front page of the clinic's website.

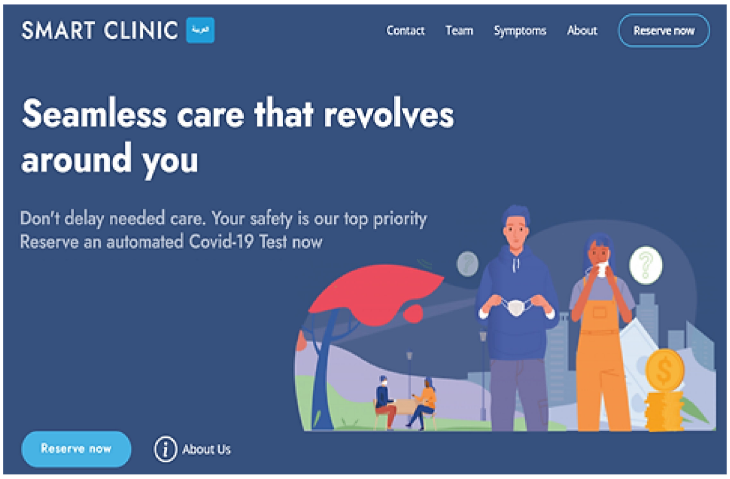


**Figure 4.** The front page of the proposed clinic's website.

There are three steps offered by the website that the patient must take when they enter the website, including the following:

1. Registration, data collection, and receiving symptoms of the patient

When a person feels tired, or some symptoms of COVID-19 are experienced, they can enter the clinic's website to register and fill out the form that includes two parts:

- Data Collection

Personal information such as Name, National ID, gender, phone number, etc. The form is shown in Figure 5.

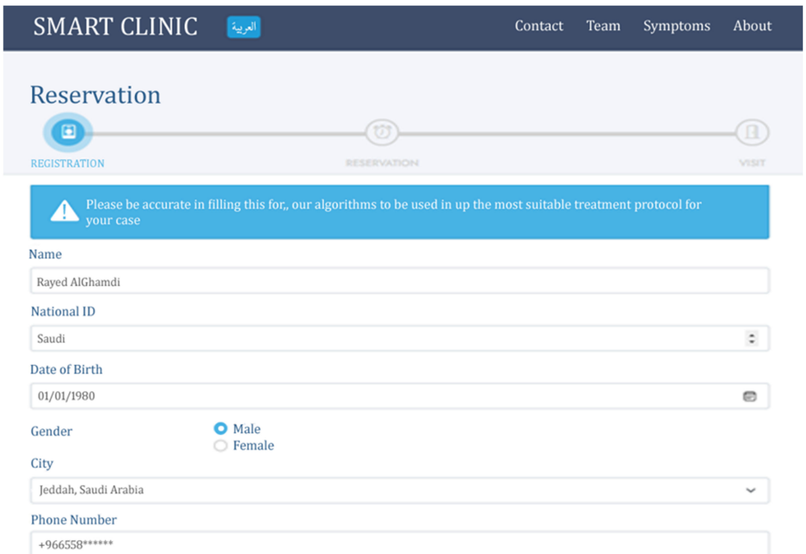


**Figure 5.** The registration form.

- Symptoms of the Patient
    - The chronic diseases that the patient suffers from (e.g., diabetes, hypertension, heart disease, obesity, cancer, asthma, etc.).
    - The symptoms that the patient is feeling (e.g., fever, cough, tiredness, loss of taste or smell, sore throat, headache, aches and pains, diarrhea, red or irritated eyes).
    - Whether the patient is a smoker or not.

  This information is used to determine the appropriate treatment protocol for each person.

2. QR code generation and determination of the appropriate appointment for the patient

   After filling out the form and answering all questions, the patient now can choose the appropriate date and time to visit the clinic for the examination. Then, the patient clicks "submit" to confirm the Reservation. After confirmation, a QR Code will be generated and sent to the patient, as in Figure 6, to be used to access the clinic. This information is stored in the database with the ID and the QR code that the patient uses to enter the clinic to do the test.

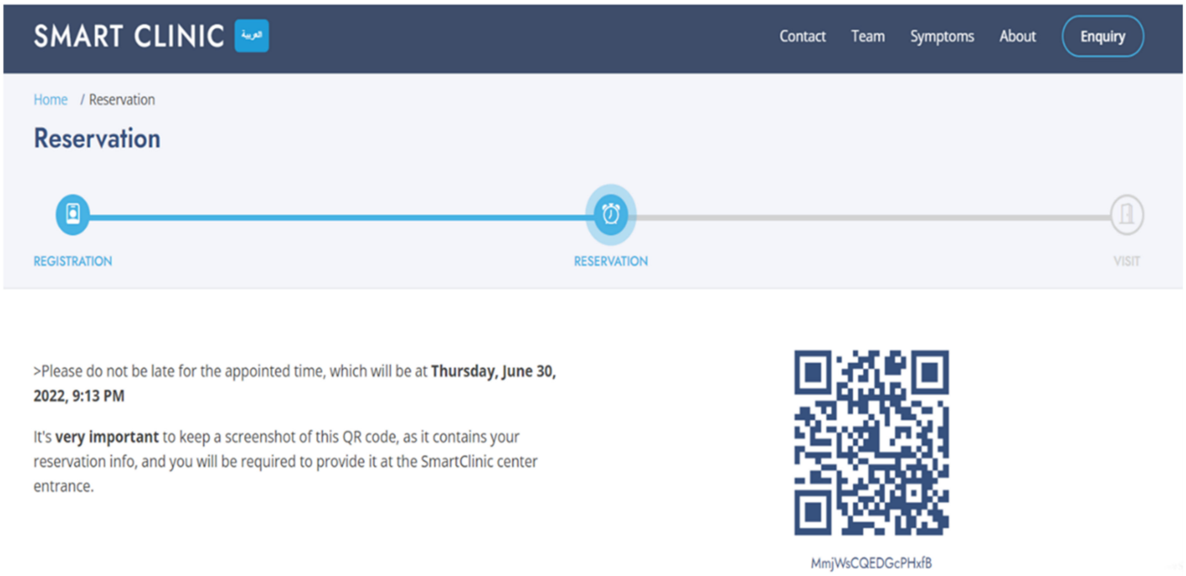


**Figure 6.** QR code generation.

3. Suggestion of an appropriate treatment protocol

   After the patient visits the clinic, a suitable protocol will be suggested based on the result.

### 3.2. Phase II: Clinic Visit

The patient can use the QR code and the ID to access the clinic by scanning the QR code using the QR code reader placed at the entrance door. The clinic structure consists of two essential stages, the sensing and measurements stage, and the X-ray stage. Based on the result of these stages, there are different scenarios. The plan of the proposed smart clinic is shown in Figure 7.

Depending on the result of patient parameter readings (temperature and $SpO_2$), there are two different scenarios: Scenario I: Normal case; then the patient will take the green path "Path (A)". Scenario II: Abnormal case, then the patient will take the yellow path "Path (B)" or the red path "Path (C)". All of these scenarios will be presented in detail in Section 3.2.2.

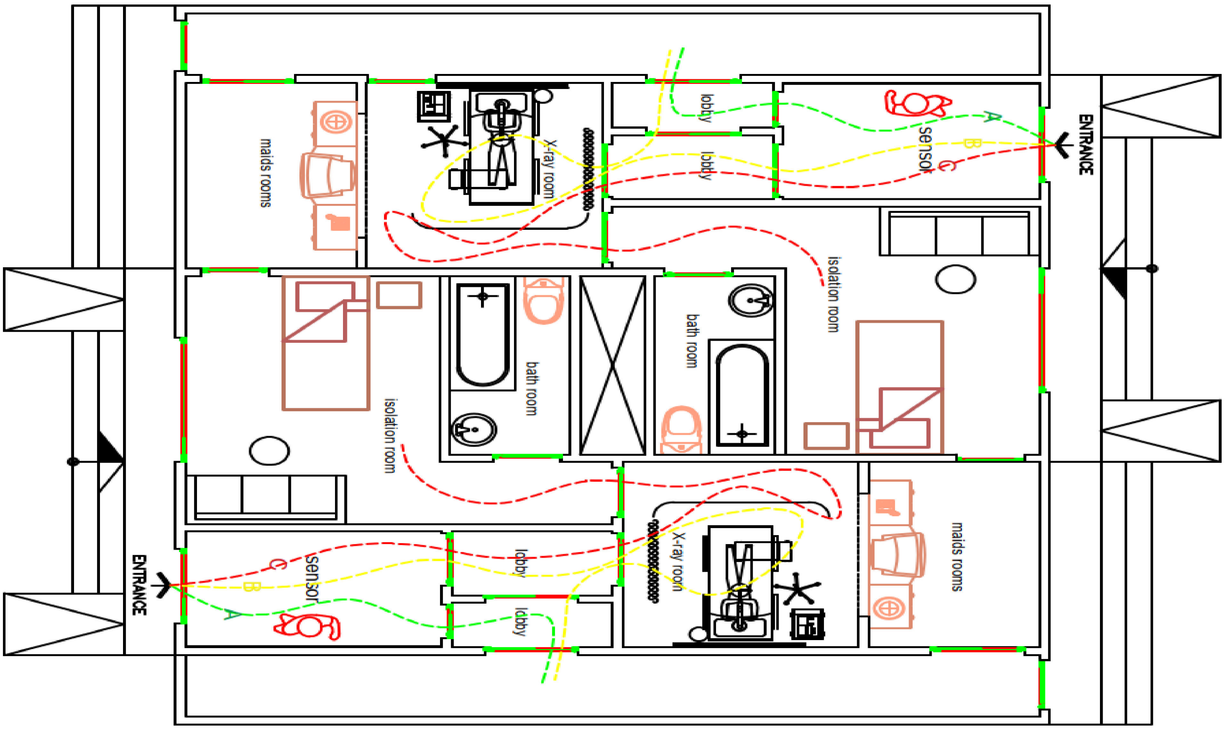


**Figure 7.** The plan of the proposed smart clinic.

### 3.2.1. Stage 1: Sensing and Measurements

In this stage, parameter readings have been taken by using different types of sensors and measurement equipment. A schematic diagram of the sensing and measurements stage of the second phase of the proposed smart clinic system is shown in Figure 8.

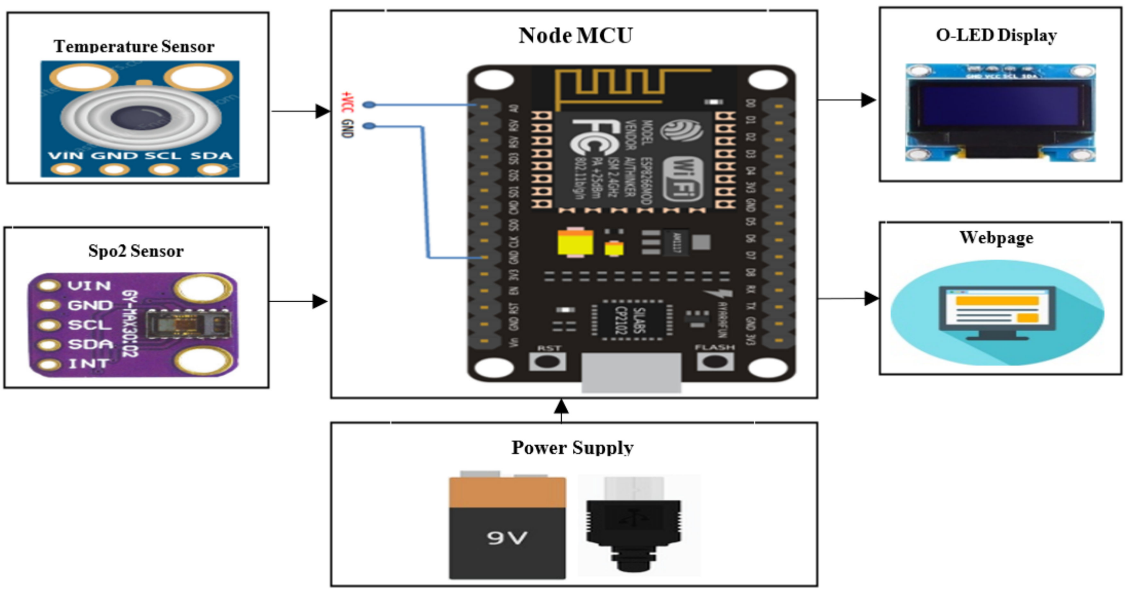


**Figure 8.** Schematic diagram of the sensing and measurements stage.

The sensing and measurements stage consists of five components: Node-MCU controller, Sensing elements ($SpO_2$ and Temperature Sensor), power supply, O-LED display, and webpage.

Node MCU Controller

Node MCU is an IoT-Platform that is a low-cost, widely used device that can connect to a Wi-Fi network and communicate with the Internet as well as build up its own network for other devices to connect to directly. In addition, it can be driven by a low-voltage power supply. This broadens the Node MCU's range of applications.

The Node MCU controller is regarded as the system's brain, accepting readings from both the temperature sensor and the blood oxygen saturation level ($SpO_2$) sensor, and displaying the results on an O-LED display in addition to having the option of uploading the results to a website.

Sensing Elements

The proposed smart clinic system architecture has two main sensors, blood oxygen saturation level (MAX30100) ($SpO_2$) and temperature sensor (MLX90614).

- $SpO_2$ Level
  - Blood oxygen saturation is calculated using the number of oxygenated and deoxygenated hemoglobin molecules, which is represented as a percentage by the $SpO_2$ parameters. According to medical research, $SpO_2$, or the percentage of oxygen in a healthy human body, should be greater than 94%, or more than 94 hemoglobin in 100 hemoglobin.
  - Pulse oximetry technology measures the amount of $SpO_2$ in the body by using infrared and red light. Oxygenated hemoglobin always absorbs infrared light while passing a red light, and deoxygenated hemoglobin always absorbs red light while passing infrared light. The $SpO_2$ data is derived from this pass-through and absorption.
  - The pulse rate is also determined using the same data since the heart rate causes the blood pressure to rise because the amplitude of the wave created by the raw data is high and low depending on the heartbeat, which is calculated and shown as the PR value. An adult human being's typical heart rate ranges between 60 and 100 beats per minute.

The structure of the pulse oximeter is presented in Figure 9.

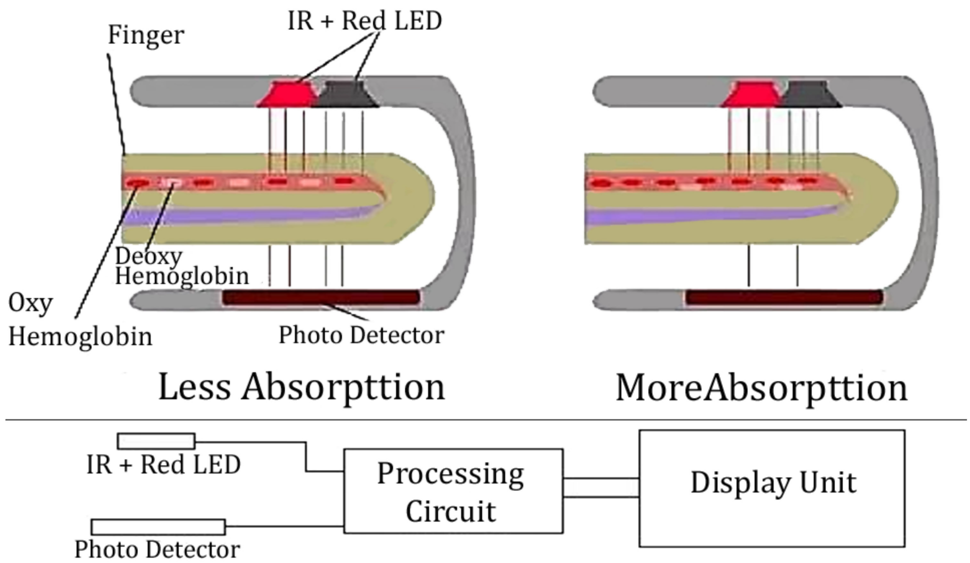


**Figure 9.** The structure of the pulse oximeter.

- Temperature Sensor MLX90614
  - The MLX90614 temperature sensor has been used in the proposed smart clinic; it is a contactless IR temperature sensor that works on the Stefan Boltzmann principle. It states that everybody radiates IR radiation proportional to their temperature.

A specific object's temperature can be measured with the MLX90614 Contactless Infrared (IR) Digital Temperature Sensor between $-70$ °C and 382.2 °C. The sensor communicates with the microcontroller using the I2C protocol and measures the object's temperature using IR rays without making any physical contact.

#### 3.2.2. Stage 2: X-ray Image

Capturing a chest X-ray image is one of the initial stages in determining whether the patient is infected with COVID-19 or not. A chest X-ray in most cases shows abnormalities, such as consolidation, caused by COVID-19 viral pneumonia. The detail of this step is presented in Section 5.

Depending on the result of patient parameter readings (temperature and $SpO_2$), there are two different scenarios:

- Scenario I: Normal case
  - The patient is considered negative when he has a normal temperature and normal $SpO_2$ reading or a high temperature and normal $SpO_2$ reading. The patient takes the green path "Path (A)" toward the lobby and leaves the clinic from the side door shown in Figure 7. Then, the sterilization process is carried out.
  - In the first state of normal temperature and normal $SpO_2$ reading, the patient can leave and go home.
  - In the second state of high temperature and normal $SpO_2$ reading, the patient can visit the medical service rooms to check up on the reason for the high temperature.
- Scenario II: Abnormal case
  - The patient is considered negative when he has a high temperature and abnormal $SpO_2$ reading. In this case, the probability of being infected with a virus or being a virus carrier is increased. Therefore, an X-ray check becomes a necessary step.
  - The patient is exposed to chest X-ray radiation. ResNet152 model is utilized in the COVID-19 detection system. The result of the X-ray image detection is either a "negative case" or a "positive case".
  - In the negative case, the patient takes the yellow path "Path (B)" toward the lobby and leaves the clinic from the side door as shown in Figure 7. Then, the sterilization process is carried out.
  - In the positive case, the patient takes the red path "Path (C)" toward the isolation rooms; according to the patient's case and registration data, the appropriate treatment protocol is selected.

This information is stored in the database as historical data for this patient for future requirements.

Some patients prefer to follow the recommended treatment protocol and isolate themselves at home. Instructions and the recommended treatment protocol are announced on the patient's pages.

## 4. The Proposed COVID-19 Detection from an X-ray Image Using Deep Learning

This section presents the proposed diagnosis of whether the patient has COVID-19 or not from an X-ray image that had been captured from Stage 2 in Section 3. The proposed algorithm depends on Convolutional Neural Network (CNN) model. The ResNet152 pre-trained model on the same type of medical images is introduced, and its efficiency is discussed. Finally, the proposed algorithm based on ResNet152 is developed. The block diagram of the proposed COVID-19 detection algorithm is presented in Figure 10.

The proposed algorithm presented in Figure 10 collects the X-ray images from different datasets. Next, the preprocessing step is applied to the collected image using several techniques to enhance these images. In the third step, the enhanced images are divided into training and testing sets. Finally, the classifier is evaluated using testing images to classify the images as positive or negative. All these steps are presented in detail in Sections 4.1–4.4.

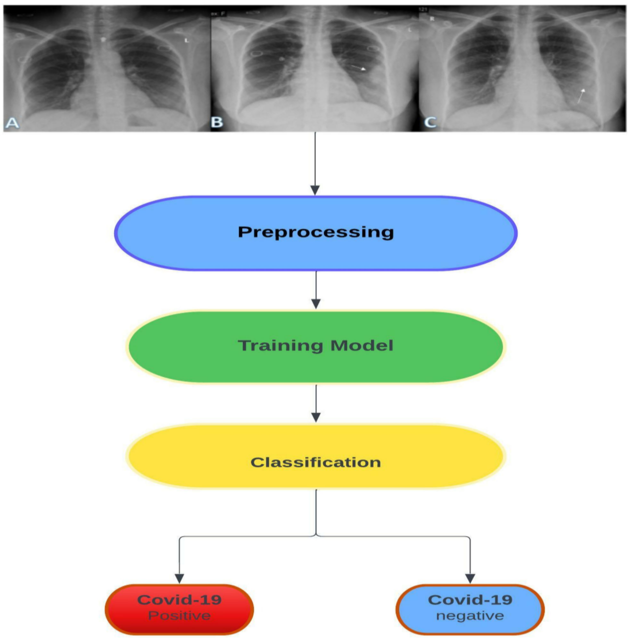


**Figure 10.** The block diagram of the proposed COVID-19 detection algorithm from X-ray images. The letters (**A**–**C**) are used to show different samples of x-ray images.

### *4.1. Dataset Construction*

There are different databases, regularly updated day by day. The dataset that had been used in the proposed algorithm is constructed from several datasets:

1. Radiopaedia [37]: open-edit radiology resource where radiologists submit their daily cases.
2. SIRM [38]: the website of the Italian Society of Medical and Interventional Radiology, which has a dedicated database of COVID-19.
3. EuroRad [39]: a peer-reviewed image resource of radiological case reports.

After the construction of the proposed dataset, the number of normal images is 43% and that of the COVID-19 images is 57%.

### *4.2. Preprocessing*

The next step after collecting the images is preprocessing these images. The preprocessing step is an important step to make all images nearly the same. First, all images are scaled to be the same size of (224 $\times$ 224) pixels. Next, some operations are applied to the images to be the same such as resizing, shear, zoom, rotation, padding, horizontal flipping, and cropping, which can be used to remove the overfitting of the data.

### *4.3. Training Model*

After preprocessing step, all images now have the same size and orientation. The images are divided into training and testing sets. The training images are equal to 80% of all images and the testing images are the remaining 20% of the images. The training images are used to train the deep learning classifier, then the testing images are used for testing the classifier. The data was trained for up to 20 epochs.

### *4.4. Classification*

Following training, the classifier is evaluated using testing images. Deep learning and the ResNet model are at the heart of the model. A Residual Neural Network (ResNet) is an Artificial Neural Network (ANN). It is a gateless or open-gated variant of the HighwayNet. The suggested model is fine-tuned using hyperparameters.

Transfer learning is the process of reusing learning from a base model to a target model, which is used in the proposed ResNet model. A previously trained model can contribute to the target model's starting point. It is frequently regarded as an optimization strategy for saving time and improving efficiency. This is advantageous when the features are universal, which means they are appropriate for both the source and target datasets rather than only the base task. The transfer learning approach has the potential to save resources such as processing power and time. Transfer learning procedures are classified into two categories. First, fixed features are removed, and then the model is trained by data from the intermediate layer. Second, the data samples are fine-tuned.

The net weights of ResNet152 are used by the ResNet and the completely linked layer at the end is replaced. Figure 11 depicts a neural network, such as a ResNet Architecture, with the input x. The essential mapping, which is accomplished by learning F, was examined (x). ResNet's activation function is at the top. Prior to the activation function, the mapping was examined. Consider mapping in terms of F(x) and residual mapping in terms of F(x) − x.

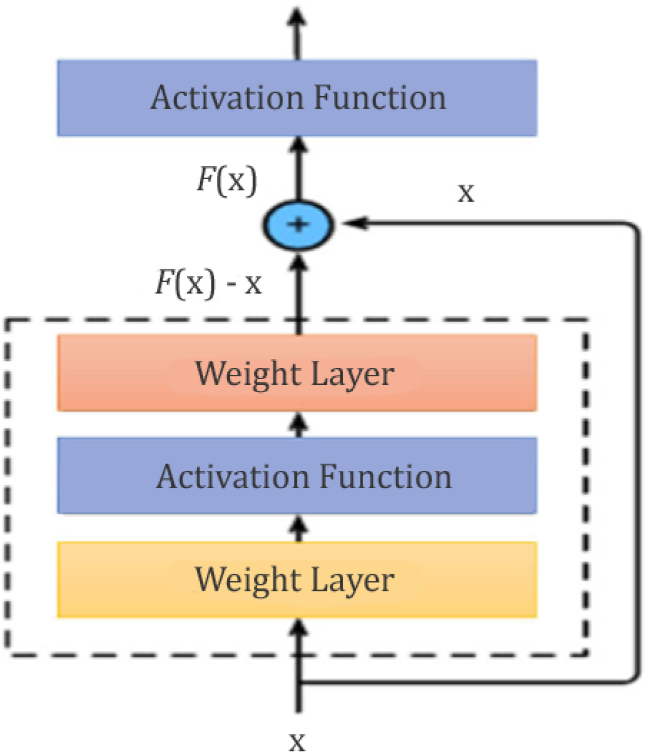


**Figure 11.** ResNet architecture.

ResNet Architecture

A Residual Neural Network (ResNet) is made up of an input layer, four stages, and an output layer, as shown in Figure 12. Each stage indicates a step in the process that is carried out sequentially. It takes input from previous stages, runs one step of the CNN, and outputs the results. ResNet is broken into five stages, with Stage 0 serving as a pre-processing of input and the latter four stages consisting of a bottleneck and having a more comparable structure. In addition, an input stem performs a 7-7 convolution, has 64 output channels, and a stride of 2. Following that is a 3-3 max pooling layer with a stride of 2. The input width and height were effectively reduced four times in this layer, but the channel size was increased to 64.

There is a down-sampling block and leftover blocks in Stage 2 and the subsequent stages. The residual blocks work in the same way as the down-sampling blocks, with the only change being the stride of the convolutions, which in this example is 1. Changing the number of residual blocks yields alternative models, such as the ResNet50 and ResNet152, which simply represent the number of convolutional layers in the network.

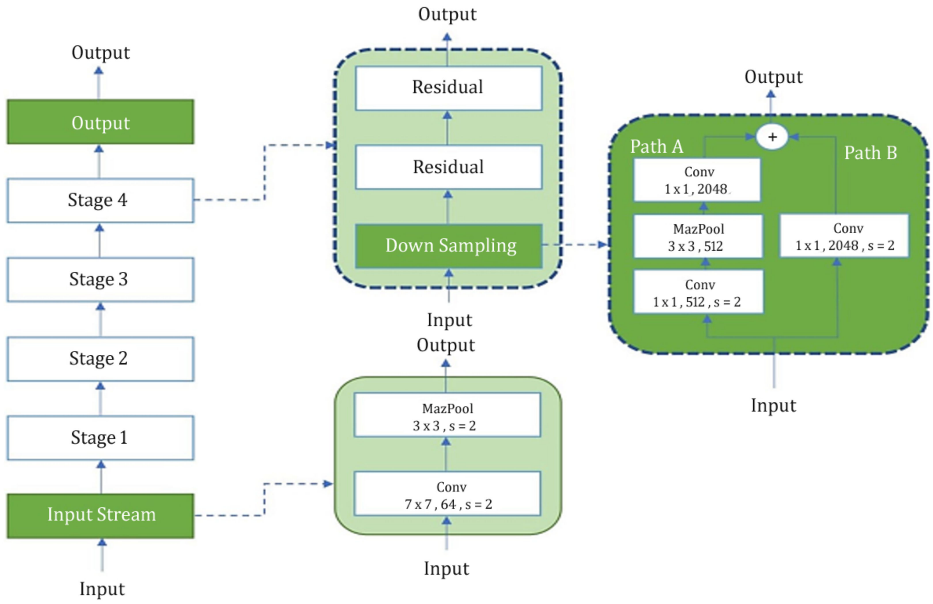


**Figure 12.** The ResNet Architecture, the convolution kernel size, and output channel size pooling layers.

Convolutional layers, an activation unit, pooling, and batch normalization are the key components of ResNet. Figure 13 illustrates these components.

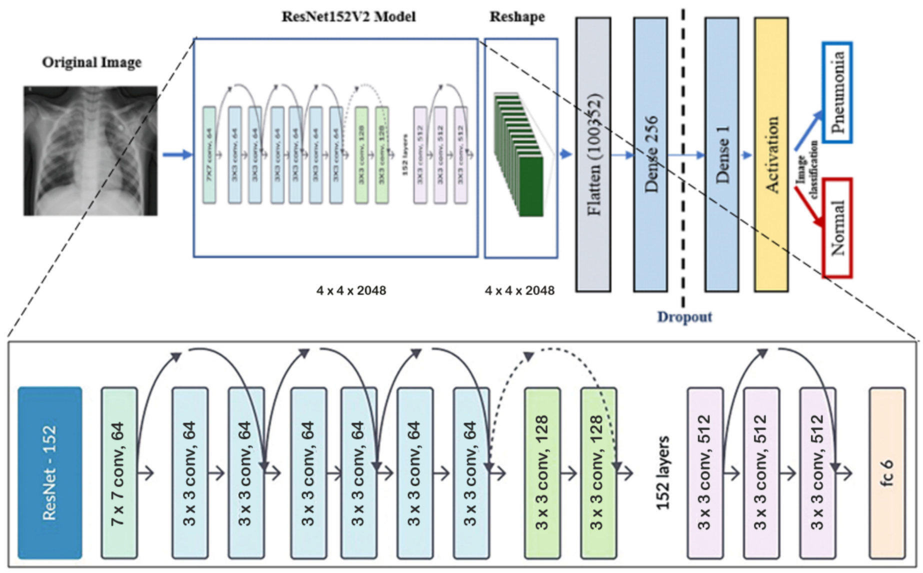


**Figure 13.** Layers of ResNet.

1. Convolution layer

Convolution layers in neural networks conduct the essential process of extracting information from input pictures. This convolution is accomplished by employing a series of filters. From the input photos, this layer generates feature maps.

2. Activation function

A transformation is performed to the output of each convolution layer in a convolution neural network. This is done to introduce nonlinearity into the framework. The Rectified Linear Activation (ReLU) function is a prominent activation function. The ReLU is a piecewise linear function that outputs the input directly if it is positive; otherwise, it outputs zero. It has become the default activation function for many types of neural networks since it is quicker to train and frequently results in higher performance. This ReLU is less expensive to compute and has better gradient convergence than other activation functions. If the input is negative, the output of ReLU is zero; if the input is positive, the output equals the input.

3. Pooling layer

The feature maps obtained from convolution operations are summarized using a pooling layer. This layer decreases the number of parameters that are considered during the training process. This also assures that the computation time is reduced. Furthermore, this layer aids in the regulation of the over-fitting procedure. The output of max pooling is the maximum value of the input element. In the case of average pooling, however, the output is the mean value of the input element.

4. Batch normalization

The batch normalization test is used to enhance the quality of convergence throughout the training period. This layer regularizes the preceding layer's output. This layer has the advantage of allowing the use of a greater learning rate.

## 5. The Proposed Blockchain-Based Pharmaceutical System

This section applies the proposed algorithm with the blockchain to the pharmaceutical supply chain as a case study as shown in Figure 14. The proposed medical kit and sensing devices are connected to physicians and Health Authority through the blockchain network.

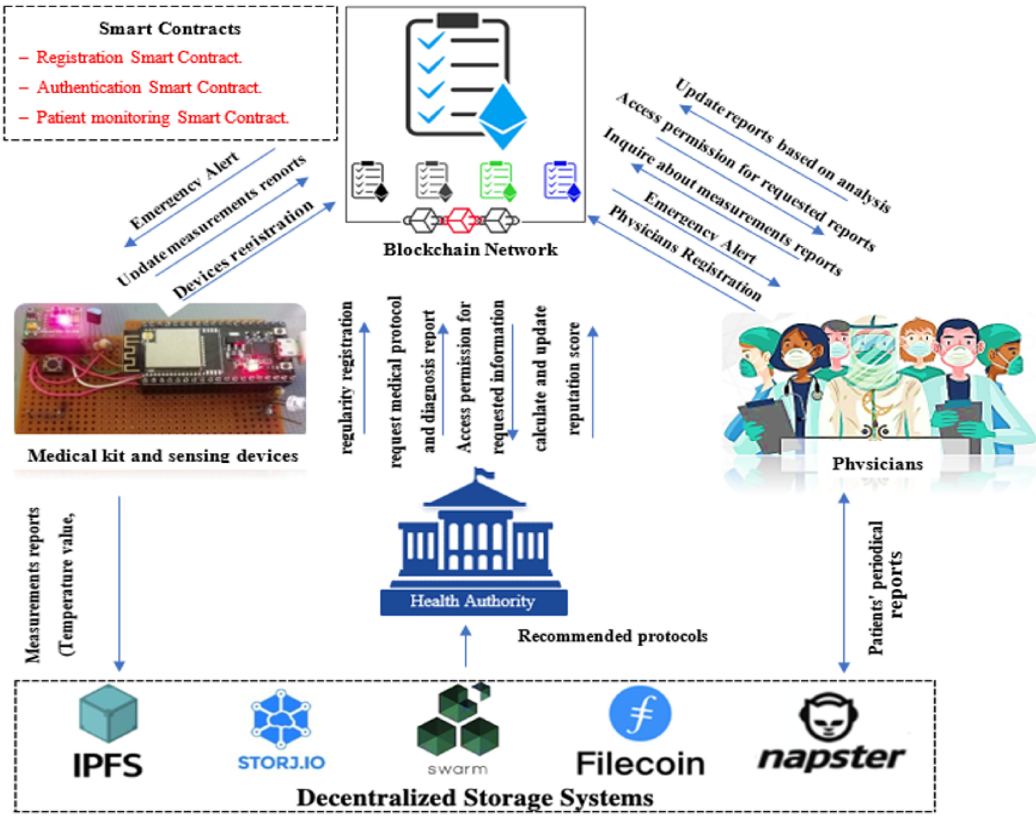


**Figure 14.** A high-level architecture for the proposed blockchain-based system for the pharmaceutical supply chain.

The structure of the proposed algorithm with the blockchain on the pharmaceutical supply chain is presented as follows:

1. The blockchain network connects the medical kit with physicians and Health Authority. The blockchain network will use several smart contracts which will be applied to the data passed through it, such as:

- Registration Smart Contract;
- Authentication Smart Contract;
- Patient monitoring Smart Contract;
- Consent Management Smart Contract;
- Drug prescription verification.

Using these smart contracts, the patient's data will be secured against any unauthorized use.

2. The medical kit and sensing devices: the medical kit has sensing devices that read the measurements of the patients. First, the kit sends device registration to the Health Authority through the blockchain network to access the login to the decentralized storage systems connected to the Health Authority. If the login fails, the blockchain network sends an emergency alert; otherwise, the registration succeeds. Next, the medical kit sends the updated measurement reports, which include Temperature value, Pulse Rate, and $SpO_2$, to physicians through the blockchain network when they ask for the reports. Finally, the kit can directly store the final measurements report in the decentralized storage systems.
3. The physicians: first, the physicians will send the registration to access the data stored in the decentralized storage systems in the Health Authority through the blockchain network. If the registration fails, the blockchain network will return an emergency alert; otherwise, the registration succeeds. Next, the physicians can inquire about measurement reports for any patient; then, they obtain permission for requested reports from the blockchain network; then, they can update reports based on patents' analysis. Finally, the physicians can directly access the decentralized storage systems in the Health Authority to update the patients' periodical reports.
4. The Health Authority: all operations are done on it through the blockchain network by the physicians and the medical kit. The Health Authority receives regular registration from physicians and the medical kit; then, it checks whether to accept or deny these registrations. After accepting the registration, it sends the requested medical protocol and diagnosis report. Next, it receives a request to obtain permission for requested information from the physicians. Finally, it calculates and updates the reputation score.
5. The Decentralized Storage Systems: it is a storage system to store the patients' data and different cure protocols. It has several storage protocols such as IPFS, STORJ.IO, SWARM, etc. The medical kit can directly send the measurement reports that include Temperature value, Pulse Rate, and $SpO_2$ to the storage system. In addition, the physicians can directly request or update the patients' periodical reports.

Any patient who wants to use the proposed blockchain-based system can take the following steps:

1. Log into the website for registration, then input some personal information and the symptoms. This information is used to determine the appropriate treatment protocol for each person. Then, the patient can choose the appropriate date and time to visit the clinic for the examination. All patient data are now stored in the data storage.
2. The patient now can visit the clinic. The clinic structure consists of two essential stages, the sensing and measurements stage, and the X-ray stage. The sensing and measurements stage consists of five components: Node-MCU controller, sensing elements ($SpO_2$ and Temperature Sensor), power supply, O-LED display, and webpage. The readings of the sensors' measurements can decide whether the patient needs to proceed to the X-ray stage or not. All these measurements are stored in the Decentralized Storage Systems in the patient's file. The physicians can see or update the patient's file anytime.
3. Now, the patient can obtain treatment and cure protocol due to the readings of the sensing elements. The cure protocol is also stored in the patient's report in the storage system.

4. When the patient visits at another time, their report will have all the symptoms they reported before together with the cure protocol he received, and any new symptoms will be stored in the same report.

## 6. Experimental Results

This section outlines the experiments and the findings. Google Collaborator, often known as Colab, carried out the trials. The Colab may provide a service using the K80 GPU (Tesla). The NVIDIA 12 GB RAM can support a 12 h operation. Google Collaboratory is an open-source cloud-based platform that distributes information such as a Jupyter notebook for deep learning. This cloud-based service was utilized for testing reasons. Furthermore, NumPy, pandas, TensorFlow, and Matplotlib were used as libraries for the experiment. In the trials, an optimizer named Adam was used for the situation of a learning rate (at the start) of 0.001. The model's training was carried out utilizing a dynamic learning strategy.

The studies were conducted using a variety of parameter values, including a factor of 0.5, patience of 5, and a minimum learning rate of 0.3–10. The validation loss was tracked using an early halting strategy with a patience value of 5. If the next 5 epochs fail to lower the validation loss, the training phase is over. The epochs were set at 20 for the experiments, with a batch size of 64.

In the output layer, sigmoid activation is present. It may be represented using the Equation (1) illustrated in Figure 15:

$$\sigma(z) = \frac{1}{1 + e^{-z}}. \tag{1}$$

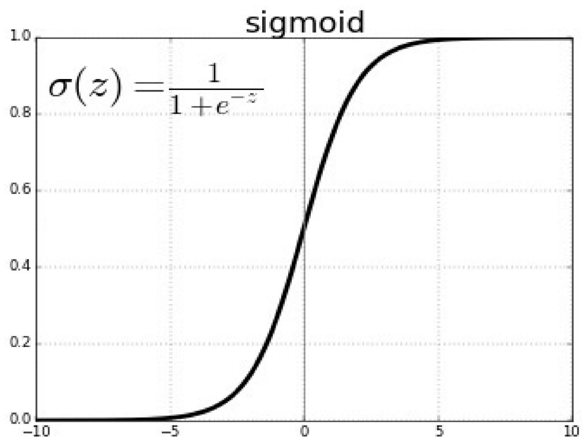


**Figure 15.** Sigmoid activation in the output layer.

The next sections describe data pretreatment, image normalization, and data augmentation. We consider data preparation first. This preprocessing enhances the visual capability of the training operation. Several variables can help enhance your vision. These are the rise and, in contrast, the elimination of high/low spatial frequency components, and the decrease in the image's noise component. As part of the preprocessing in this study, the images are resized to (224 × 224) pixels and their intensities are normalized. The intensity of image pixels is standardized from their original 0–255 values to a normal distribution using the "min–max normalization" approach in intensity normalization. The bias factor is thereby eliminated, resulting in uniform distribution.

Figure 16 presents the accuracy curve for 20 epochs of the ResNet152 model. The peak value of these curves could be determined. Figure 17 depicts the loss curves for 20 epochs of the ResNet152 model. It can be observed that while epochs are increasing, the losses are decreasing. The most accurate result for this algorithm was obtained while the value of the loss was low.

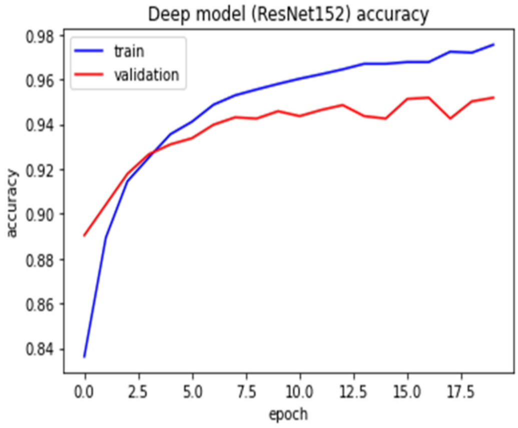


**Figure 16.** Accuracy curve based on 20 epochs for ResNet152.

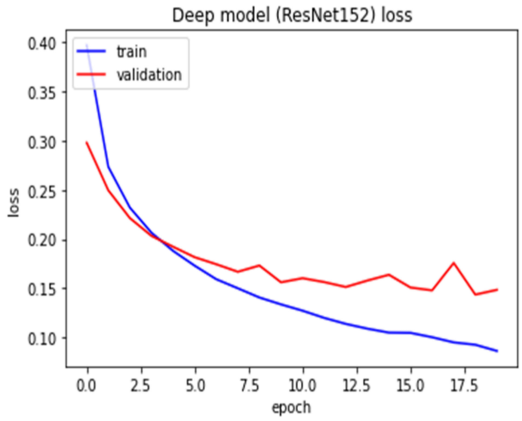


**Figure 17.** Losses of model based on 20 epochs for ResNet152.

This model (ResNet152) was selected after comparing this model with other models such as linear and DenseNet121. The ResNet152 provides higher accuracy than the other algorithms. Many different models were tested to see which is a better fit for this problem. They all incorporate transfer learning, which utilizes a pre-trained model to use as a base, and layers are added afterward to adapt to the problem we are working with. This reduces the time needed to train the network. All models utilize a different base model; however, each is a Convolutional Neural Network (CNN). CNN is the base structure for image classification tasks as it can extract features from images—edges, lines, and other shapes.

The proposed model was first based on a linear model as a baseline; it was a very simple model with only one trainable hidden layer. A pre-trained ResNet is used as a base, but all the parameters are set to be untrainable. The proposed model was improved by using deep learning and adding more hidden layers to improve the performance.

DenseNets require fewer parameters and allow feature reuse; they result in more compact models and have achieved state-of-the-art performances and better results across competitive datasets as compared to their standard CNN or ResNet counterparts. Table 2 shows a comparison between linear, DenseNet121, and ResNet152 models.

**Table 2.** Comparison between linear, DenseNet121, and ResNet152 models.

| Model | Metric Parameter | | | |
|---|---|---|---|---|
| | Training Accuracy | Training Loss | Validation Accuracy | Validation Loss |
| **Linear** | 95.7% | 13.8% | 94.3% | 16.4% |
| **DensNet121** | 88.5% | 30.3% | 87.4% | 30.5% |
| **ResNet152** | 97.5% | 8.6% | 95.2% | 14.9% |

Figures 18–21 present training accuracy, validation accuracy, training loss, and validation loss, respectively, for linear, the DenseNet121, and the ResNet152 models.

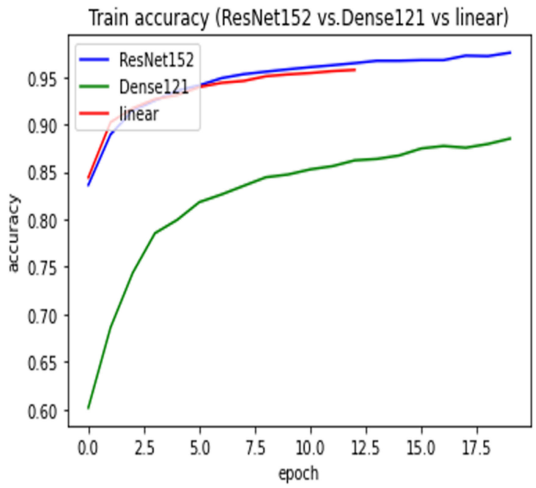


**Figure 18.** Training Accuracy curves for ResNet152, Dense121, and linear models.

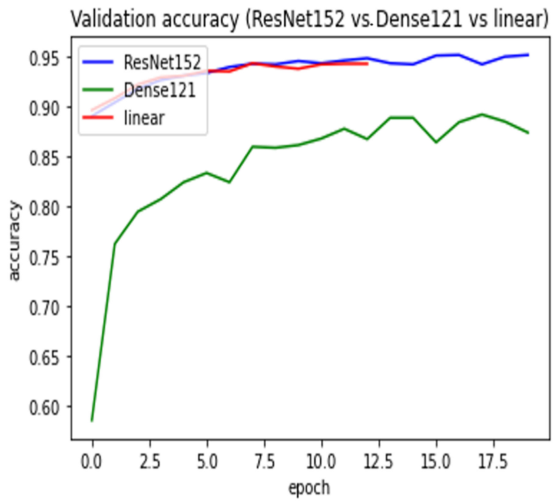


**Figure 19.** Validation Accuracy curves for ResNet152, Dense121, and linear models.

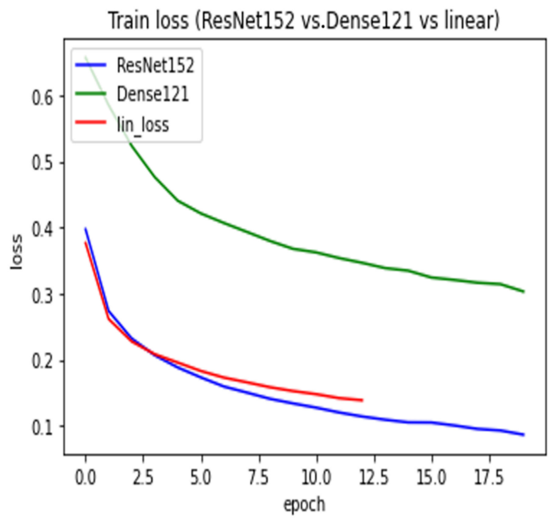


**Figure 20.** Training Loss curves for ResNet152, Dense121, and linear models.

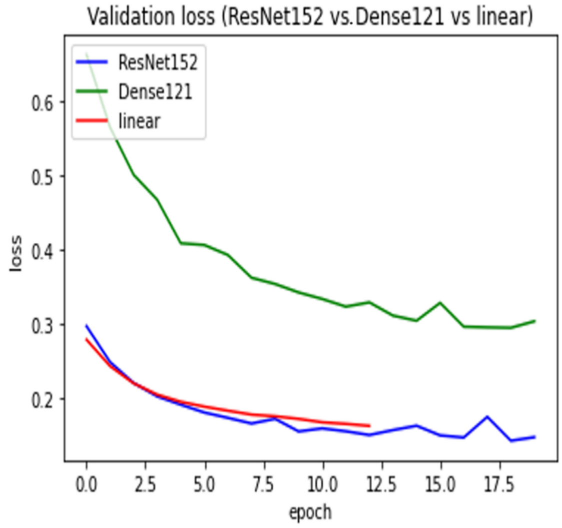


**Figure 21.** Validation Loss curves for ResNet152, Dense121, and linear models.

## 7. Result Discussion

Table 2 shows that the linear model provides higher training and validation accuracy with lower training and validation loss compared to the DensNet121 model. When the linear model improved after the implementation of deep learning in the ResNet152 model, the training and validation accuracy increased to 97.5% and 95.2%, respectively, and the training and validation loss reduced to 8.6% and 14.9% respectively.

Figures 17 and 18 show that the ResNet152 model provides higher training and validation accuracy when the number of epochs increases (20 epochs) than the Dense121 and linear models.

From Figures 19 and 20, the ResNet152 model provides lower training and validation loss when the number of epochs increases (20 epochs) than the Dense121 and linear models.

## 8. Conclusions

IoT is one of the emerging fields that has been recently used in many applications, including healthcare. However, IoT systems, especially in healthcare, suffer from different vulnerabilities and attacks. This paper designed an IoT smart healthcare system based on blockchain technology for a secure and efficient system. It is designed to work independently without human intervention, saving medical staff from any exposure to disease. This paper also proposed COVID-19 detection using a deep learning algorithm from an X-ray image. The transfer learning ResNet152 model is utilized to develop a fully automated and robust COVID-19 detection system. The paper also presents the proposed blockchain-based pharmaceutical system. The proposed systems and algorithms are compared to the most recent algorithms and show higher performance quality in terms of accuracy. The proposed algorithm produces higher training and validation accuracy with lower training and validation loss than the other algorithms using 20 epochs. The training and validation accuracy reached 97.5% and 95.2%, respectively. For future work, the proposed system needs to be compared with more algorithms. In addition, it is planned to deploy the proposed framework in a physical hospital as a pilot project to be generalized if proven effective. More deep learning algorithms could be examined for better performance.

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