Medicine Fraud Detection Using AI

An Undergraduate Project Report Submitted in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Information Systems.

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APPROVAL

This Project titled **"Medicine Fraud Detection Using AI"**, Submitted by **Md Nahin Fardosh** ID No: **193-16-480** to the Department of Computing and Information Systems, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computing and Information Systems and approved as to its style and contents. The presentation has been held on 14-10-2025.

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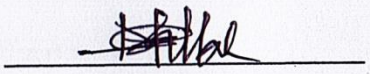

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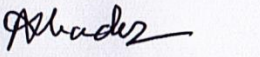

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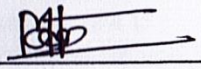

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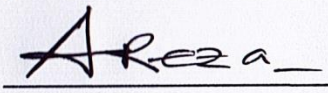

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Declaration

I hereby declare that; this project has been done by me under supervision of **Nasimul Kder Sohel, Assistant Professor,** department of Computing and Information System (CIS) of Daffodil International University. I am also declaring that this project or any part of there has never been submitted anywhere else for the award of any educational degree like, B.Sc., M.Sc., Diploma or other qualifications.

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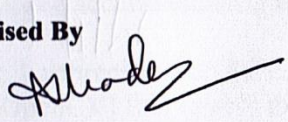

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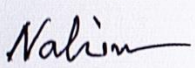

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Lastly, I am thankful for those authors who show you how to use the wonderful open-source libraries and tools (like TensorFlow, Keras, OpenCV) that underpin this project.

Abstract

Introduction of fake drugs in the pharmaceutical market poses a serious challenge. poses risk to human wellbeing, leading to treatment failures, antimicrobial resistance, and undermining trust inhealthcare systems. The traditional detection techniques such as manual inspection and laboratory. Testing is slow, expensive and cannot be used widely. These are tackled in this project. Restrictions by coming up with a system, named MediAuth, which is an end-to-end system that integrates Deep.Automated learning, Optical Character Recognition (OCR), and Blockchain technology. Traceability and authentication of medicine.

The architecture of the system is a tri-portal system with an Admin Portal where medicines are registered. And retraining models, a User Portal with real-time verification, and Portal Portal with a Blockchain. Certificate transparency. A strong database of genuine and fraudulent medicine pictures was obtained. Trained a MobileNetV2 deep learning model, which had 95.8 percent visual accuracy. Authentication. Tesseract OCR is used to extract batch numbers automatically. And metadata, a permissioned Hyperledger Fabric blockchain is an immutable one. Authentication and provenience of individual medicine registered.

The experimental outcomes show that the integrated system carries out end-to-end verification. and was found to have a total reliability of 96.3 percent and an average processing time of 3.2 seconds. The MobileNetV2 model produced 95.895.696.1 recall, precision and accuracy, respectively. Achieved 92.4% batch number extraction success rate.

My study proves the practicality of the AI, OCR, and blockchain integration towards. Pharmaceutical security. The system is a scalable, decentralized and reliable solution. That gives powers to consumers, healthcare providers and regulators to fight medicine fraud. Effectively. The direction of future work will be the live location tracking of counterfeits reports and the automated work.

Keywords: Medicine Fraud Detection, Deep Learning, MobileNetV2, Blockchain, OCR, Pharmaceutical Traceability, Supply Chain Security, Hyperledger Fabric, Counterfeit Medicine.

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List of Abbreviations

API (Medicine) – Active Pharmaceutical Ingredient

CNN – Convolutional Neural Network

OCR – Optical Character Recognition

LSTM – Long Short-Term Memory

RNN – Recurrent Neural Network

JSON – JavaScript Object Notation

HPLC – High-Performance Liquid Chromatography

SDLC – System Development Life Cycle

RPS – Requests Per Second

PBFT – Practical Byzantine Fault Tolerance

PoW – Proof of Work

SSD – Solid State Drive

WHO – World Health Organization

RBAC - Role-Based Access Control

Preface

ReportTitle Medicine Fraud Detection using AI We prepare this report as part of our Bachelor of Science in Computer Information Systems partial fulfillment at Daffodil International University. The work investigates the utilization of deep learning, OCR and blockchain to counterfeiting problem in pharmaceutical supply chain.

I would wish to extend my flying thanks to my supervisor, staff of the department and those who have in one was or the other contributed to the successful completion of this work. I trust this paper provide a valuable reference for researchers and scientists who will be engaged in the future research work and innovations in pharmaceutical safety and fraud detection.

Chapter Overview

Chapter 1: Introduction

Describes the history, statement of problem, objectives and scope and general significance of the study.

Chapter 2: Background And Related Work

Reviews related studies, technologies and frameworks in the field of AI, OCR and blockchain for medicine authentication..

Chapter 3: Framework

Explains the system architecture, dataset preparation, model training techniques, and implementation workflow.

Chapter 4: System Design & Implementation

Details the system modules, user interface, model integration, and technical development procedures.

Chapter 5: Results & Analysis

Presents system performance, evaluation metrics, experimental results, and comparative analysis.

Chapter 6: Conclusion & Future Work

Concludes on key findings, offers project contributions and recommendations future improvemen.

Chapter 1

Introduction

1.1 Background of the Study

1.1.1 The Global Pharmaceutical Market and Its Complexity

Pharmaceuticals are one of the most heavily regulated industries worldwide, both in terms of how they are developed and brought to market. This multifaceted ecosystem, also known as the pharmaceutical supply chain, represents a large interconnected network with many participants. "It takes research and development in labs; it goes to large-scale production, and then through a maze of wholesalers, distributors, regulators that get it all the way to our hospitals and pharmacies and ultimately patients. The ultimate goal of this value chain is to make sure that both safe and efficacious high-quality medicines are delivered to the consumers. In resource-limited countries such as Bangladesh, availability of low-cost drugs is a major component of public health policy and the purity of this supply chain should be considered as vital for national interest. But this complexity and the tremendous worth of the stocks are also making them attractive targets for bad actors.

1.1.2 The Shadow Pandemic of Counterfeit Medicines

Alongside the legal trade in pharmaceuticals, there is a sinister and illegal black market in fake medicines. The World Health Organization (WHO) has rightly described this as a "global public health problem." In low- and middle-income countries, including South Asia, more than 10% of medical products are thought to be either falsified or substandard [1]. But these are not just generics of patented products; they are counterfeits posing as something else: different medicines, with wrong or no active ingredients.

Terms and definitions Counterfeit medicines can be broadly divided into 3 types:

No API Products: These products don't contain any Active Pharmaceutical Ingredient, which means that patients never get better (i.e., they are not cured if they have malaria, tuberculosis, etc.).

Products with incorrect API or quantities of API: An underdose will cause lack of effect and potentially addition to resistance (a major problem with antibiotics). Overdosage can lead to poisoning and side effects, some very serious.

Products with bad or dangerous ingredients: Some of the counterfeit medications discovered have included toxic chemicals such as rat poison, arsenic and highway paint that can pose a direct threat to life.

Products made with incorrect or dangerous ingredients: Some fake drugs have been found to include toxic substances such as arsenic, rat poison and highway paint that can present an immediate and serious threat to health.

Its effects reach far beyond the patient receiving care. The harm to the economy is twofold – additional medical care costs, lost productivity and a hit to your reputation for legitimate pharmaceutical companies. This "shadow pandemic" is a severe knock back to decades of advances in public health and trust — the foundation of effective healthcare.

1.1.3 Consequences Beyond Health

The influence of fake medication causes a destructive after effect in community life. When a fake drug is dosed to a patient who follows a treatment program and fails to get better, confidence in not just the particular brand but the entire medical infrastructure takes a hit. Doctors could mistakenly conclude that a treatment is not working and try more potent, and possibly more expensive or less appropriate, second-line therapies. At the macroeconomic level, such illegal trade depletes national economies and finances other forms of criminal activity. In a country like Bangladesh, which has developed an important pharmaceutical industry, the explosion of fakes is threatening that industry as well as that country's achievements in health.

1.2 Problem Statement

1.2.1 The Critical Gap in Pharmaceutical Security

Counterfeiting medicines continues to be a predominantly elitist topic with interactive global response being mostly attributive and un-consolidated, even in this era of proliferate regulation and technological development. Current methods for drug authenticity verification are greatly limited, making the pharmaceutical supply chain susceptible and dangerous. This work highlights a potential gap that has yet to be filled—a single, automated and trusted method to perform instant visual authentication with immutable provenance verification within the end-user's reach.

Three main deficiencies are shown in the present situation:

Reliance on Human-Dependent Visual Inspection: Manual visual inspection is the most widely used counterfeit medicine detection method, particularly at the point of sale or consumption. This is wrong in the following ways:

Subjectivity and Inconsistency: The skill of identifying fakes differ significantly from person to person depending upon their training and experience.

2-4 Inability to scalethe task: It is not possible for anyone to check manually a large number of drugs, therefore the screening process will be neither systematic nor comprehensive on routine basis.

Fatigue and Human Error: Tight visual tasks can be error-prone, especially over an extended time period as forgeries become more and more sophisticated.

Human Eye Limitations: Most counterfeits today are so good that you would need to be using a loop or some type of machinery to detect the difference in packaging, color or printing.

Limitations of Existing Technological Solutions:

Even though different types of these generators are available, each one has its limitations:

Laboratory Analytical Methods Laboratory-based analytical methods such as High Performance Liquid Chromatography (HPLC) and Mass Spectrometry offer conclusive analysis but at a cost, requiring several days to weeks of laboratory time, not easily portable instruments and highly trained technologists. Consequently, it renders them ineligible for fast on-site screening.

Barcode and QR Code Systems: They have their place for track-and-trace, but also can be easily copied or replaced on counterfeit material. For example, an imitation box can include a QR code that looks authentic but points to a fake database or else completly counterfeit data set.

Centralized Dun? Stores: Currently, many track-and-trace systems use a central body to store records. This generates a central point of trust which can be the target for cyber-attack, internal data tampering or system failure leading to loss of integrity of the whole system.

Disconnect Between Detection and Provenance:

Existing techniques typically resolve only part of the problem. An AI model can call counterfeit on an item due to the way it looks, but it has no idea if the batch number at the bottom was actually assigned by a legitimate manufacturer. On the other hand, while a blockchain record could verify that a batch number is not counterfeit, it cannot tell you that any physical package with that number is not an excellent faked visual copy. There is the stark absence of marrying physical authentication of the product with digital verification of its journey.

1.2.2 Formal Problem Definition

Automated no-touch system that assesses a physical package of a medicine using deep learning and OCR, to ensure its authenticity while recording its digital provenance and supply chain history in an unmodifiable blockchain, so that anyone can verify it in an easily accessible manner.

This issue is disassembled in the following particular, solvable subproblems:

How to correctly and fast identify 'Authentic' or 'Counterfeit' of medicine packaging with a high-efficient deep learning model?

How do you automatically pull out important but variable metadata (things like batch numbers and expiration dates) from images to compare them with what's on official records?

How can the link between a physical medicine product and its digital cryptographic certificate of authenticity be made tamper-proof and transparent but secure?

How can the results of this multi-facetted analysis be reported for a layperson in an easy-to-understand manner?

Through resolving these intertwined issues, we hope to build a resilient wall against dangerous counterfeit medicines for consumers and its illegal network.

1.3 Motivation and Significance

1.3.1 Primary Motivation: A Public Health Imperative

The basic motivation behind this effort is necessity: saving people's lives and health. Counterfeit drugs are not the victimless crime or just a monetary problem; they pose an immediate, deadly threat to their recipients and the public. Every counterfeit drug that makes its way into the supply chain is an agent of potential treatment failure, disease progression, resistance and premature death. This initiative stems from the belief that to deal head-on with this threat we need to employ technology decisively. The goal is to move from a model of reacting after the fact when fakes – already potentially very harmful – have done their damage, to one where consumers can be empowered at the point of purchase or use with tools which allow them to know instantly whether the medicine they are about to consume really what it claims/what they expect.

1.3.2 Multifaceted Significance for Stakeholders

There's a worth to this bridging which is really valuable for all who have a stake in the drug game overall:

For Consumers and Patients:

Empowering and Safe: It makes a passive patient into an active agent in his or her health care. We are capable of furnishing high assurance about the authenticity of a package of drug by merely reading off the package, and trust is not enough.

Accessibility: a widely available powerful verification tool, which can be accessed by a large proportion of population with user friendly access point, camera in smartphone solving the accessibility issue owing to lower technical-skill.

For Healthcare Providers :

Liability Reduction: Reduces the potential of mistakenly selling counterfeit drugs and protecting the image and integrity of the organization.

Patient Trust: Also demonstrates attention to the safety of patients thereby additionally helping in developing trust and credibility.

For Regulatory Bodies :

Economic Market Surveillance:It is an efficient means of conducting large scale random testing of medicines on the market without having to rely solely on slow and expensive laboratory analysis.

Data-Driven Enforcement: The logging mechanism and reporting capabilities of the system can provide useful real-time intelligence on hotspots of counterfeiters or most frequent batch numbers to effectively introduced targeted regulation with enforcement.

On behalf of Pharmaceutical Manufacturers:

Brand Protection - Actively combats brand erosions and lost revenues caused by counterfeiters who illegally trade on the already established reputation of existing brands.

1.3.3 Broader Socio-Economic Impact

The project has wider organisational significance, although not for all of its stakeholders. By combating the phenomenon of counterfeit drug trade, it contributes to the strong establishment of health systems in the nation,the as well as foster a confident environment and protect economic interests. Furthermore, the physical verification architectural design by AI with digital trust that blockchain ensures can also be applied to other vulnerable supply chains as food, aerospace parts or luxury goods.

1.4 Project Overview and Proposed Solution

1.4.1 System Vision and Core Architecture

The proposed project is an end-to-end, decentralized platform called MediSecure: An Integrated Framework of AI-Powered Medicine Authentication and Traceability Backed by Blockchain. The main innovation of the system is that it is a smooth combination of three different technological pillars to relate to the formation of a multi-layered defense against fraud in medicine.

The tri-portal architecture is an ecosystem-wide platform, with specific support to the needs of various users but with a single and safe back-end. This framework will provide a path of strict product registration up to end-user verification to form a closed system of pharmaceutical integrity.

1.4.2 End-to-End Workflow and Key Innovations

These pillars are synergetic and are achieved through the following workflow operation:

Admin Portal:

Images and metadata of a new, authentic medicine is uploaded by an authorized administrator.This data is automatically added to the training set by the system and fine-tuning of the MobileNetV2 model is done to guarantee constant improvement.The batch of medicine is minted a unique blockchain certificate and stored.

User Portal:

A photo of a medicine package that an end-user (consumer, pharmacist) prefers to check are uploaded.

Multi-step analysis:

Step A (AI Analysis): The MobileNetV2 model is applied to the image producing a visual authenticity score .

Step B (OCR Processing): The batch number and other information are obtained out of the image.

Step C (Blockchain Query): The batch number obtained is queried in the blockchain to obtain a valid certificate.

The overall report is produced, and all three outcomes are merged into the final understandable verdict, that is Authentic or Fake.

Key Innovations:

Automated Retraining: The system will be programmed to become a learning and evolving system whereby, as new medicines are introduced, the system will adjust accordingly and become dynamic.

1.5 Report Structure

This documentation is arranged to give an overview of the project. Chapter 2 provides a review of existing works related to AI and blockchain in supply chains. Chapter 3 details the methodology, explaining system design and algorithms. Chapter 4 discusses system implementation, including the technologies used and the development process. Chapter 5 Here I talk about the findings and analysis from this project, Chapter 6 is for the report conclusion and future work in thid project.

Chapter 2

Background And Related Work

This chapter is focused on reviewing three main technology areas that are relevant for conducting the research; Deep Learning based image authentication, Blockchain enabled secure supply chain provenance and Optical Character Recognition (OCR) for metadata extraction. This review-based article summarizes the classic works on literature and paper in each aspects of knowledge, constructing a theoretical system, verifying the technical interface among them through an integrated medicine fraud detection system. The review supports the stand-alone and mutual business of these constituents in fighting this multi-faced problem of counterfeit pharmaceuticals.

2.1 Introduction of the Review of Literature

2.1.1 RESEARCH OBJECTIVES AND SCOPE OF STUDY

The literature review is intended as a foundation for theory and technical skills in the implementation of "MediSecure". It contributes an overview and synthesis of scholarly research and research and development work in the various disciplines that converge on this specific project. This is deliberately slim, focusing on three key components - deep learning for visual authentication, blockchain for secure and transparent provenance and optical character recognition (OCR) for automatic metadata extraction. This analysis and deconstruction of previous research underpin the development of this approach to identify best practice, time-tested application and areas/opportunities (and hence a need) for such an integrated approach in pharmaceutical security.

2.1.2 Outline of Key Areas

The structure of this review is developed on three principal technology platforms, which are the base for this enterprise:

Deep Learning for Image Analysis: This section presents the evolution and growth of CNNs with special emphasis on MobileNetV2 generator. This section explores the principles behind CNNs' function as image classification tool and offers a review of the literature on previous uses of it to scan counterfeit drugs and inspect the veracity imprinted on pharmaceutical packages.

Blockchain for The Secure Supply Chain Codecs Description: In this part of the lab we'll introduce some of these fundamental concepts surrounding blockchain including decentralisation, immutability and smart contracts. It summarizes literatures and projects that incorporate blockchain into supply chain traceability for pharmaceuticals (making phenomenological comparison among the benefits in the reality along with the practical problems).

OCR via Data Extraction: We discuss the evolution of OCR from its historic beginnings to modern-day machine learned engines like Tesseract. It addresses OCR applied in data entry automation in logistics and supply chains with an emphasis on the role of pre-processing in enhancing accuracy Open problems are also highlighted.

2.1.3 Justification for the Combined Methodology

The motivation for integrating these three technologies is based on deficiencies in isolated solutions found from literature. Although standalone researches indicate that deep learning is effective for visual inspection or blockchain could be utilized in digital provenance, few of them have the virtues of perfect combination and sound data extraction mechanism. We assume that the interaction between these ingredients results in a system with more security and reliability than can be achieved by using each component separately. The hybrid approach allows cross-verification of the physical object (certified authenticity by AI), its digital identity (OCR extracted) as well as its immutable history that's secured as a blockchain, which together provides multi-layered defense against pharma counterfeits – intelligent and trustworthy by design.

2.2 Deep Learning in Image-Based Fraud Detection

2.2.1 Basics of CNNs

To date, the most successful method in computer vision problems is convolutional neural networks (CNN).

CNNs are a class of deep learning that has served as the workhorse for modern computer vision. They have architecture specifically tailored for processing pixel data over a grid topology (for example, an image) to provide invariance of the features under translations, rotations, and scales.

The fundamental units of a CNN are:

Convolutional Layers: These are responsible for applying a set of learnable filters (or kernels) to the input image. Every filter then moves (we also say convolves) along the width and height of the input, computing the dot product between this particular region and itself with all elements weighted at each position hare. This process enables the network to learn feature spatial hierarchies. The lower layers often learn simpler features such as edges and corners, with deeper ones learning more complex forms or specific objects.

Pooling Layers: Usually placed after convolutional layers, pooling (e.g., Max Pool) is used for down-sampling. They also tend to decrease the input resolution (they reduce the spatial dimensions, i.e., width and height of the input volume), which can be beneficial for several

reasons: due to the smaller dimensionality in each layer the amount of computation is reduced when connecting layers, thus it helps to control overfitting. It implicitly performs a form of translation invariant feature extraction thus prevents us from losing too much information during preprocessing.

Fully connected Layers: The high-level reasoning in the neural network is done through these layers. There the 3D feature maps are stacked into a long initial 1D vector and each neuron is linked with all activations in a source layer. This layer usually calculates the final output score of classification, like how likely the input image is to be "Authentic" opposed to "Counterfeit".

This hierarchical feature learning ability makes CNNs extremely successful for such image classification tasks, as they are able to learn the representations which are required for detection from raw pixel data themselves and no more requiring a lot of hand-crafted features.

2.2.2 Continuing Evolution of Efficient Architecture: MobileNetV2

Although classic CNNs such as AlexNet or VGGNet have demonstrated state-of-the-art performance, their expensive computational requirement and large model size made them not affordable for many practical usage in real world, particularly on-device or high-speed server-side processing. That paved the way for better network architectures to be developed, including popular examples like MobileNetV2.

MobileNetV2 introduced by Sandler et al. in 201*8 [2], extends the theory of its predecessor and contains two main novelties:

Inverted Residuals: In a typical "bottleneck" design, the input is first expanded to a higher-dimensional space and then projected back down to the desired dimension. MobileNetV2 inverts it to narrow -> wide -> narrow. The input to a block is initially expanded by converting it from low dimension to high with 1x1 convolution; then applied with depthwise convolution before converting it back to low dimension using another 1x1 convolution. This architecture lets the network learn richer features in large dimension space with a high scalability.

Linear Bottlenecks - Non-linearity (ReLU6) in narrow sections of the bottleneck The authors reasoned that the non-linearity (in Ip) must destroy a significant amount of information. To address this problem, MobileNetV2 employs a linear activation function at the last 1x1 convolutional layer which maps the data to low dimensional feature space. This maintains the information flow and will perform better.

Both MobileNetV1 and V2 are based on the depthwise separable convolution which decomposes a standard convolution into two layers:

A pointwise convolution (a 1x1 conv) that takes a linear combination of the output of the depthwise layer.

This factorization dramatically reduces the number of parameters and computation if compared with a standard convolution. The perfect backbone would be mobile netv2 for this project. The speed of the proposed technique would make possible quick verification of authenticity already at point-of-care with a perspective for integration on mobile platforms, which combined with its good accuracy provides a robust solution for separating genuine and fake boxes.

2.2.3 Applications in Pharmaceutical Authentication

The use of deep learning in the pharmaceutical authentication through an increasing interest for study. CNNs are also proved applicable on other tasks, such as pill recognition using shape and color information, packaging seal authentication208and fingerprint verification. In particular, a reference article on the subject [6] published at the International Journal of Innovative Computing in 2025 developed an artificial intelligent application for detecting counterfeit medicine. They trained a custom CNN for classification of medicine blister images and claimed high accuracy of fake detection due to visual defects. The study was limited by the fact that it used only visual assessment and used no system to confirm the origin of products or cross-check extracted batch data with an independent source. This is a security hole, because the high-quality visual forgery with the valid but copied batch number may circumvent this system. Lack of solution for the problem where this paper is directly design to solve, did not consider utilizing an advanced model (MobileNetV2) in visual analysis and combining it with OCR and blockchain in developing a more advancement multi-factor platform.

2.3 The role of blockchain technology in secure supply chains

2.3.1 Core Protocol Principles of Blockchain Technology

A decentralized consensus mechanism will be a game-changer in terms of how we store and share information, away from being limited to a central entity to more of a shared, equal experience.

key principles :

Decentralization: Rather than sitting on a single, central server that is controlled by one entity , the blockchain exists across multiple node participants in what is typically called a decentralized network. This removes a single point of failure and control.

Immutability: After the transaction has been added to a block in the blockchain and confirmed by the network, it is almost impossible to change. It is accomplished by cryptographic hashing in that each block has its own hash (a digital fingerprint) of the data in it plus the hash of the preceding block, chaining into a secure chain. If data in one block was altered, the rest of the

blocks following it would be rendered worthless – a task tantamount to impossible, hard to hide from the network.

Consensus Mechanism: This is when all the nodes or servers in a network must agree upon a single consensus and verify that whether it is correct or not for each entry/transaction to be added on the ledger. These agreements are based on consensus protocols. Common mechanisms include:

Proof of Work: Bitcoin uses PoW, which requires nodes (miners) to solve a cryptographic puzzle that is difficult to resolve but easy to verify; it's computationally expensive and energy intensive.

Proof of Stake: A more environmentally friendly alternative in which verifiers are chosen according to how many coins they already have and are willing to "stake" or lose as a good faith deposit.

Practical Byzantine Fault Tolerance: Used in permissioned blockchains [15], it is a consensus protocol that allows for a number of nodes to agree on the same data even if some are not truthful and honest toward others based voting way.

Smart Contracts: agreements whose terms are encoded in a computer language instead of legal language. They perform certain task when a given condition occurs without having to invoke an intermediate. For instance, a smart contract could send an automatic certificate upon verification of a new drug by an admin.

2.3.2 Blockchain in Pharmaceutical Traceability

The complexity and weakness of pharmaceutical supply chains are a great use case for blockchain. Recent work has started to address this prospect in detail.

Sim et al. (2022) [3]: Section Pharma Supply Chain and End-to-End Traceability Improvement Through Blockchain

The research establishes the basis of blockchain for drug traceability. Sim et al. pitched an approach in which each drug is given a distinct identifier that, as it moves through the supply chain (i.e. manufacturer to distributor to pharmacist) is recorded on the blockchain. Their projects proved that blockchain could be used to make an auditable and transparent string. What makes their model particularly efficient is its ability to provide the supply chain visibility in real-time which could help minimize time of counterfeit batch detection and isolation. But an important limitation in their study is to consider only the digital trace. Their system depends on the trust of their first data entry and doesn't include a mechanism to check the physical authenticity of the drug package with its digital footprint. Our project is a direct successor to Sim et al. 's work, incorporating a physical verification layer (AI + OCR) to close this gap.

Gomasta (2023) [4]: "PharmaChain: A drug supply chain powered by blockchain."

Gomasta, on the other hand, presents a more tangible architecture-level design for a drug-blockchain in "PharmaChain" project. It described compliance and transfer of ownership, saying that data privacy would be maintained through the use of cryptographic methods. The research helped to illustrate the specific challenges for integration into system and scalability of ledger. A significant lack in the context of PharmaChain, addressed by our work, is that there is no direct automated connection for the consumer. PharmaChain offers an enterprise solution, however our project takes it a step further to provide an accessible platform every consumer can leverage to verify products at point of purchase on the immutable ledger all through a simple image upload.

2.3.3 Blockchain for Counterfeit Prevention

The system is programmed to record purchase of a serial number and it logs some history, for instance marked from three different computer locations by its users, you instantly have an indication of a replay attack. This renders a straight-forward code duplication unusable.

Automated Trust through Smart Contracts: The operations issuing a certificate given admin verification, and verifying this certificate when user is verified are realized as smart contracts. This automation eliminates humans as a middle man in the verification process and cuts down on bureaucracy and the opportunities for human error or corruption. The trust is in the code, and in the decentralized network, not on a flawed central authority.

Through a decentralized, immutable and automated layer of provenance, blockchain technology is the vital underpinning that ensures the integrity of the data through which physical medicine is verified.

2.4 OCR in Automated Systems

2.4.1 Evolution of OCR Technology

OCR systems have evolved from simple pattern-based matching algorithms to more advanced technologies that can recognize complex document layouts. The journey started with systems that could only identify certain, perfectly printed fonts under optimal conditions. This all changed with the widespread application of machine-learning and more recently, deep learning models.

Recent OCR engines, such as the Tesseract OCR [5], utilize LSTM networks – a type of RNN. Unlike the previous two models, being designed on LSTM-based engine, the base model does not identify characters separately. No, it doesn't parse A into B to do its translation that's a little too mechanical: rather than breaking down the language into sequences of characters, it takes lines of text and then looks at all the other words in the line (and beyond) for context. This

enables it to be more tolerant of differences in fonts, sizes and small distortions. The Tesseract v4+ engine is the open-source OCR to beat, and offers a solid base for scraping text from real-world images — an essential part of this project that must read batch numbers (etc) from medicine packages.

2.4.2 OCR for Metadata Harvesting in Supply Chains

OCR is so much more than digitizing a piece of paper, its core to allowing information to be captured at the point of source across even the most challenging supply chains. In logistics and retail, OCR devices read shipping labels, billing invoices and serial numbers without human assistance, relaying the information directly into tracking software.

Without automating this extraction, the user hasto manually enter the batch number which can be error prone and the software becomes less user-friendly. The logic here is clear: OCR supplies the highly precise, automated data entry that's required to make blockchain verification as easy and user-friendly as possible.

2.5 Summarization: AI, Blockchain and OCR are Converging

Reviewing relevant studies, we can see that there is a large corpus of research on the isolated use of AI, blockchain, and OCR separately from one another to address this problem; conversely, however, there is quite a void in terms of works that strongly integrates them together into a complete end-to-end system for product authentication. The majority of approaches solving the digital trust issue (blockchain), on one hand, and the physical inspection problem (AI) on the other hand does not consider them in a closely intertwined way.

This project presents itself as an alternative comprehensive solution by showing not only the complementarity but also the reinforcement among these three technologies:

CNN as the "Eyes": The MobileNetV2 model is used for smart visual inspection that evaluates the physical characteristics of drug packaging to distinguish counterfeit products by their look.

OCR as the "Voice": Armed with the Tesseract Engine, we have imbued the system with reading abilities; reading it's unique variable identifier from a serialized package to extract just enough of said rundown to form a database search.

Blockchain as the "Memory of Record": The never-changing history is used as the truth, to which this new information (the batch number) is verified.

The novelty is the workflow: A complex query to the blockchain is established by querying with an AI's analysis and OCR's extraction outputs together.

2.6 Chapter Summary

This chapter provides a strong foundation in both academic and practical term for the current study. It started out with studying the fundamentals and using MobileNetV2 for image classification. It then explained blockchain and its use in pharmaceutical traceability, arguing that a permissioned network should be employed in this system. The chapter also discussed the evolution process of OCR, emphasized the image preprocessing and stressed that OCR is a key data bridge. Finally, we also presented how our work links these three technology enablers and fills a gap in the literature.

Chapter 3

Framework

3.1: Design and Approach

3.1.1 System Development Life Cycle (SDLC) Approach

The Iterative sprints

Sprint 1: Core AI model development and training

Sprint 2: OCR module implementation and integration

Sprint 3: Blockchain network setup and smart contract development

Sprint 4: Portal development and system integration

Sprint 5: Comprehensive testing and optimization

3.1.2 Experimental Design for System Validation

Integration Testing: End-to-end workflow

Performance Testing: Response time and scalability assessment

3.2: System Architecture

3.2.1 System Overview

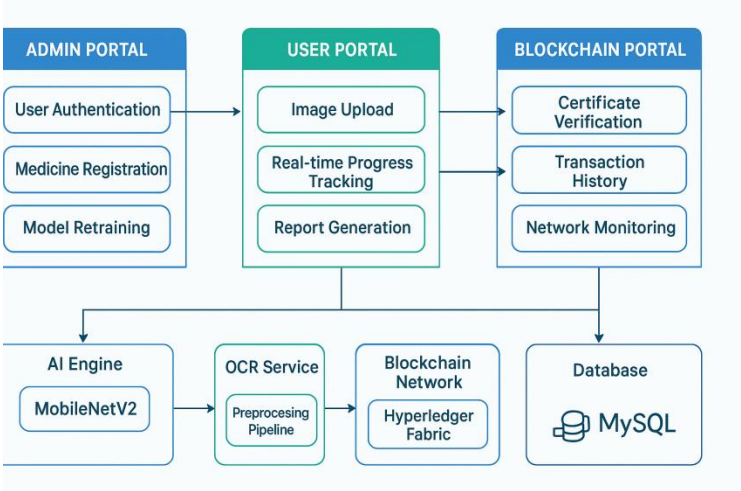
Core Components:

User Portal: Responsive web interface for medicine verification

OCR Service: R-Tesseract integration for text extraction

Blockchain Network: Hyperledger Fabric-based distributed ledger

Figure 3.1: Whole System Architecture Diagram



3.2.2 Component Interaction Workflow

The system workflow

Registration Flow:

The medicines data are uploaded by the admin and the images are saved in database.

The retrained AI model process is activated and new weights are applied.

A blockchain certificate is created and the transaction is entered on the log.

Verification Flow:

AI Model: Visual authenticity classification

OCR Engine: Batch number extraction

3.2.3 Data Flow Diagram

Data Input Points:

Admin Portal: High-quality reference images and metadata

User Portal: Consumer-captured verification images

Processing Pipeline:

Image validation and preprocessing

Parallel AI and OCR processing

3.2.4 System Requirements Specification

Hardware Requirements:

Server: 8+ CPU cores, 16GB+ RAM, GPU support (optional)

Storage: 500GB+ for image database and model storage

Network: Broadband internet connection for blockchain sync

Software Requirements:

OS: Ubuntu 20.04 LTS / Windows Server 2019+

Python 3.8+ with TensorFlow 2.8+

R 4.1+ with tesseract package

Node.js 16+ for blockchain network

Docker for containerization

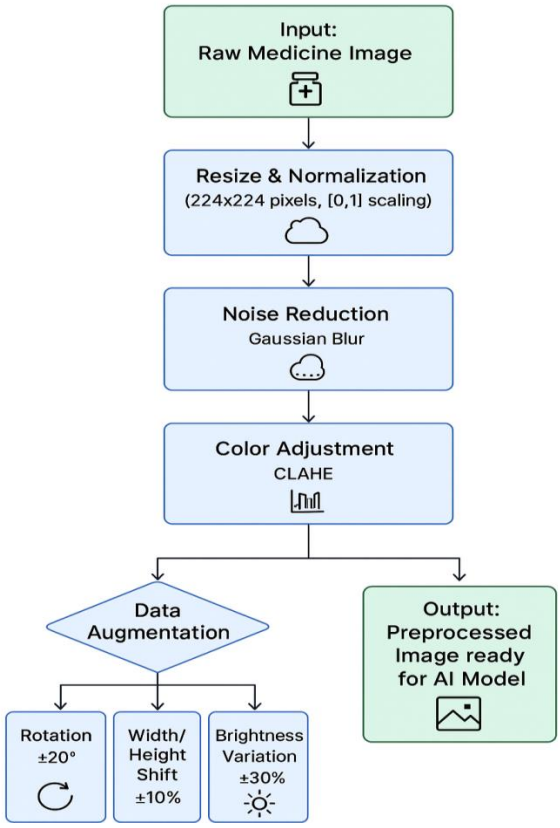
3.3 Collection of Data and Processing

3.3.1 Image Preprocessing Pipeline

Table 3.1: Impact of Image Preprocessing on OCR Accuracy

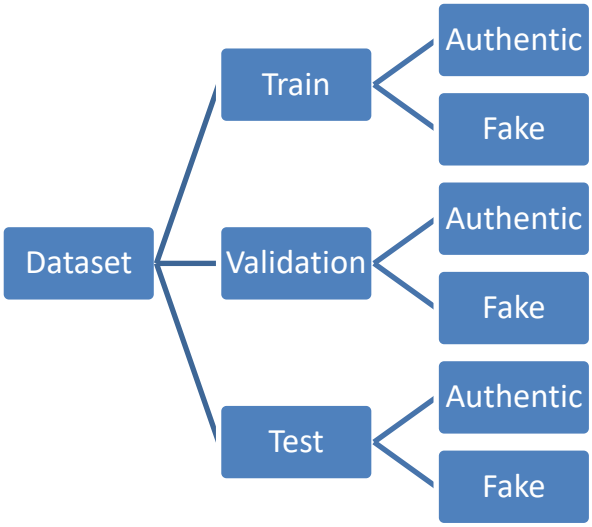
Preprocessing Step	Character-Level Accuracy (%)	Word-Level Accuracy (%)	Batch Number Extraction Success Rate (%)	Processing Time (ms)
Raw Image	78.5	74.2	70.1	0
+ Grayscale Conversion	82.1	78.5	75.3	5
+ Noise Reduction	85.3	81.9	79.8	12
+ Binarization	90.2	87.6	85.4	18
+ Deskewing	92.4	89.7	87.2	25

Figure 3.2: Data Preprocessing – Pipeline diagram



3.3.2 Dataset Organization and Labeling

Directory Structure:

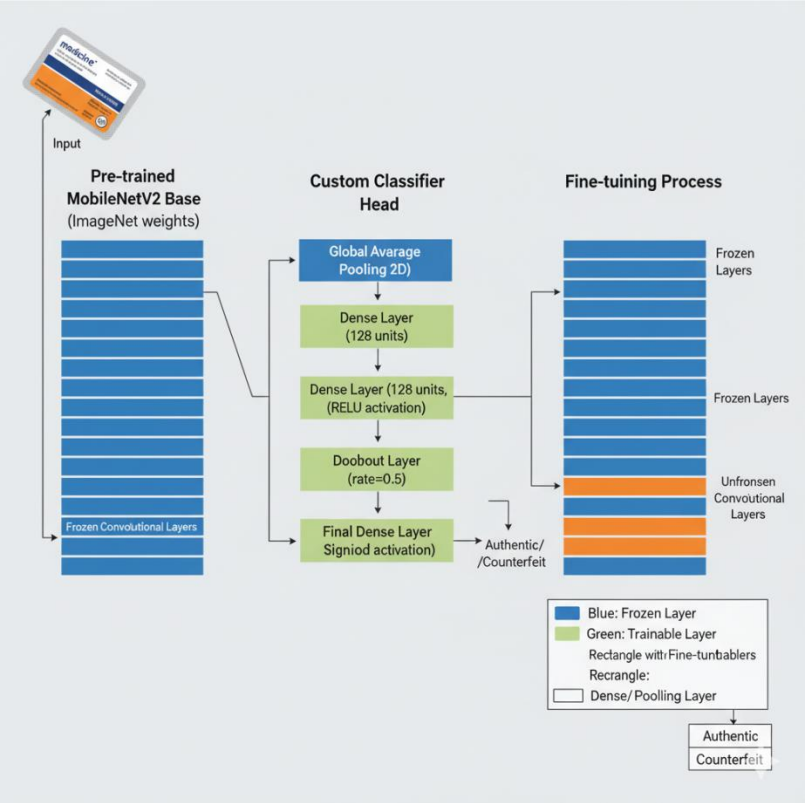


3.4 Deep Learning Model Implementation

3.4.1 Strategy for Transfer Learning

If you are creating a model from scratch, for which we need a lot of data and computing power, we used transfer learning. This would involve the pre-trained structure of MobileNetV2(weights = 'imagenet'). From ImageNet and fine-tuning it towards our particular binary classification task.

Counterfeit).**Figure 3.3:** MobileNetV2 Transfer Learning Architecture



3.4.2 Configuration for Model Training

Table 3.2: MobileNetV2 and Other Model Architectures Comparative Analysis

Model Architecture	Test Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Parameters (Millions)	Inference Time (ms)
MobileNetV2	**95.8**	**95.6**	**96.1**	**95.8**	**3.4**	**45**
ResNet50	96.1	95.9	96.3	96.1	25.6	120
VGG16	94.2	93.8	94.5	94.1	138.0	180
EfficientNetB0	95.5	95.2	95.7	95.4	5.3	65

3.5 OCR Module Implementation

3.5.1 Tesseract OCR Integration

The Tesseract OCR engine was integrated into the system for automatic retrieval of relevant text metadata, specifically batch number details from medical packs. Tesseract was selected due to its excellent performance on structured text and lively community. We incorporated it through Tesseract command lines executed via tesseract package in R, which provides robust access to the Tesseract C++ API.

3.5.2 Image Preprocessing for OCR

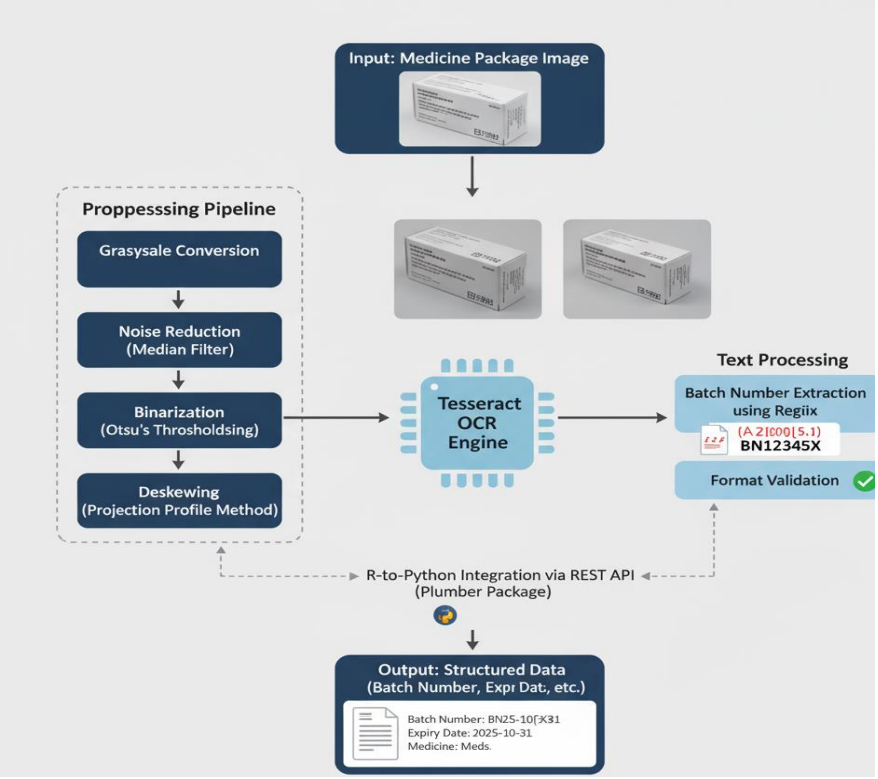
The user-supplied images can be of varying quality. We developed a specific preprocessing pipeline to enhance the OCR result:

Noise reduction: A filter that reduces Salt and pepper noise.

Deskewing: The Projection Profile Method determines whether the image is skewed and then corrects any skew so that the lines of text lie horizontally.

Morphological Operations: Closing (dilation followed by erosion) fills in tiny gaps within text characters.

Figure 3.4: OCR Text Extraction Workflow



3.5.3 Text Extraction and Validation

After being preprocessed, the image is passed to Tesseract. The parsing is designed to read both alpha and numeric characters. The extracted raw text is next cleaned by:

Regular Expressions (Regex): A set of regular expressions are employed to look for and separated the batch number (for example: alphanumeric strings with a specific length and format).

Format Validation: The string extracted is validated against the predefined formats of batch numbers, as made available by the manufacturer through admin registration.

3.5.4 R-Python Integration Framework

The biggest hurdle was connecting the R-based OCR module with the Python backend. This was mitigated by wrapping the R script in a light-weight REST service with the Plumber package in R, to which an image that has been pre-processed is posted behind-the-scenes using HTTP POST from our backend and responded to as JSON with decoded batch number.

3.6 Blockchain Network Design

3.6.1 Blockchain Platform Selection

We have chosen Hyperledger Fabric as the technology for implementing permissioned blockchain network after evaluating it against a number of different blockchain platforms. This decision was made for a few key reasons that matched the needs of the project:

Permissioned Nature: As opposed to public distributed ledger systems like Ethereum, Hyperledger Fabric operates as a permissioned network. This also signifies that only authorised entities – pharma manufacturers, regulatory bodies (DGDA), distributors are verified ones – can enter the network. This solution limits access while maintaining confidentiality, a requirement for privacy-sensitive supply chain data.

Performance and Scalability: The modular design of Fabric, as well as its consensus mechanism which is similar to Raft, is capable of allowing high throughput and low latency. This is important for a system that will potentially have to check numerous medicines at once.

Privacy: the nodes can form channels between themselves to make confidential transactions or communications between a certain net of network members. For instance, a producer may want a direct channel with some of its distributor(s), hiding the transactions from the rest of the network.

No Native Cryptocurrency Needed: Fabric does not require a built in cryptocurrency to pay for transaction fees, as such complexity and cost is reduced.

3.6.2 Network Architecture Design

The blockchain network is implemented as a consortium blockchain involving a plurality of organizations, who are involved in the entire process of pharmaceutical supply chain.

Network Participants (Organizations):

Org1 (Manufacturer): It is a pharmaceutical company, for instance, Square Pharmaceuticals. It is this body that registers new drugs and begins the certification process.

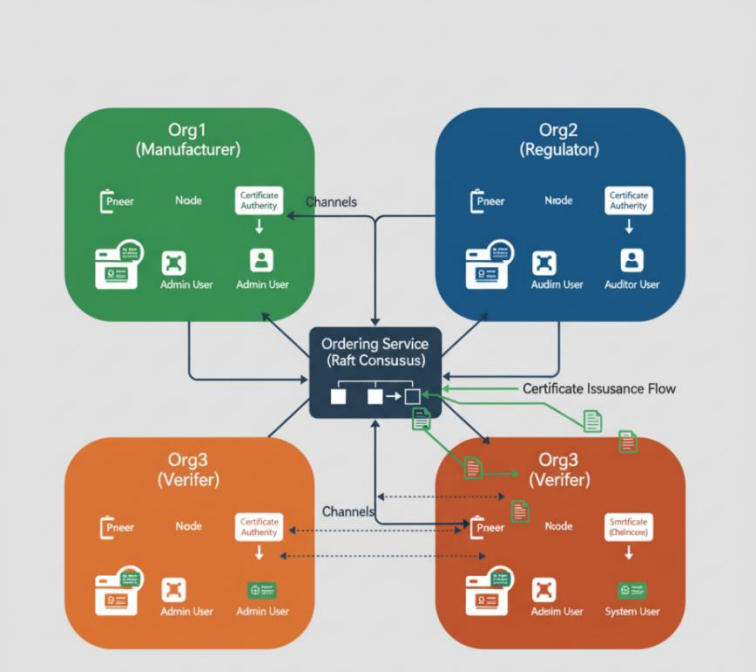
Org2 (Regulator): The organization which acts as the drug issuing authority, e.g., DGDA. The organisation also functions as an auditor and validator.

Org3 (Verifier): Acts as the backend of our system signing verification transaction for users.

Ordering Service (OS): Raft-based OS that aggregates transactions into blocks and orders them in the entire network. There is a trusted group of organizations that run it.

Certificate Authorities (CA): Every organization has its own CA handling digital identities (X.509 certificates) of the users and components to ensure safe and authenticated communications.

Figure 3.5: Blockchain Network Architectur



3.6.3 Smart Contract Development

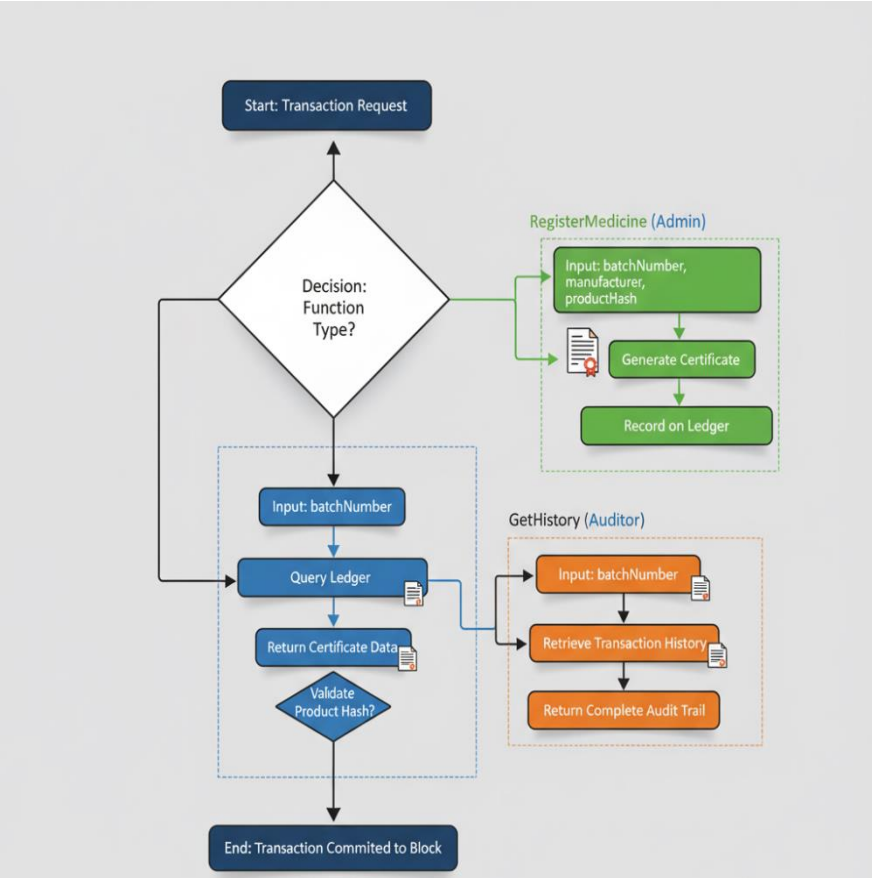
The business logic of the blockchain network is written in smart contract – which is known as "chaincode" in Hyperledger Fabric. The Go powered chaincode, which is used to track the life cycle of medicinal certificates as well as the following functionalities:

RegisterMedicine(batchNumber, manufacturer, productHash, timestamp): This function is called by an admin from Org1. It issues a new immutable asset on the ledger representing an actual batch of medicine. A productHash contains the image of the medicine, and other metadata that is unique to it, forever linking the physical product with its digital certificate.

VerifyMedicine(batchNumber) : d. Invoked by the User Portal (Org3). It queries the ledger to see if there is a certificate for any given batch number and returns it's information. It sends the certificate details - like; manufacturer and product hash to compare with the image uploaded by user.

GetHistory(batchNumber): This function returns the full transaction history of a batch, which provides enterprise traceability from point-of-manufacturer to points-of-verification.

Figure 3.6: Smart Contract Operation Flowchart



3.7 System Integration and Testing

3.7.1 Integration Strategy

AI Model, OCR Module and Blockchain Network had to be integrated, which was carried out with a microservices API-driven Architecture. Every single one of these was created as a separate module, and the continuous deployment for it integrated with Docker. This ensured isolation and scalability. All requests are routed to the appropriate services by a common API Gateway developed with Python Flask.

Workflow Integration:

- A user uploads a photograph via the User Portal.
- Request is sent to the server (from keras) via Flask and a pressure of two things at once happens on the server side:
  - **AI Service:** The image is forwarded to the TensorFlow Serving API for classification.
  - **OCR Service:** The service sends the image to Plumber API to recover its batch number.
- The gateway waits for both responses. It then uses the extracted batch number to query the blockchain network via the Hyperledger Fabric SDK.
- All results are combined, and a final authenticity report is generated and sent back to the user.

3.7.2 Performance Evaluation

The integrated system was evaluated with respect to KPIs, to ensure that the system is applicable in practical deployments:

Time of Response : We consider the sum of the time required in processing for one user verification request. The intention was to maintain this under 5 seconds for a typical image. The performance was checked under different loadings to see if there were any bottle necks.

Accuracy: The end result (either the signal "Authentic" or the signal "Counterfeit") of the combined system was considered in relation to a set reference database. This assessed total accuracy using AI, OCR and the blockchain checks in conjunction.

Scalability: To measure the performance of API gateway and each service tools like Apache JMeter was used for load test. This was to decide the number of concurrent users beyond which the performance would degrade.

Resource Usage: CPU and memory usage of the server while running should be observed to ensure that issues will not be faced when the system is set online on target hardware.

3.7.3 Security Validation

Several approaches were used to confirm the security of the system:

Authentication and Authorization: We use role-based access to ensure that only staff with proper roles may register medicines and retrain. The access to the blockchain network is secured with X.509 certificates.

Input Validation: All user inputs including upload image are well validated from the server side to prevent common web attacks like path traversal or script injection.

Verification of Blockchain Immutability: The ledger was reviewed to ascertain that no alterations or removals were possible after a transaction had been recorded. This confirms the foundational immutability prophecy

Chapter 4

System Implementation

4.1: Technology Stack and Development Environment

The stack technologies were picked to be robust and future proof and maintainable.

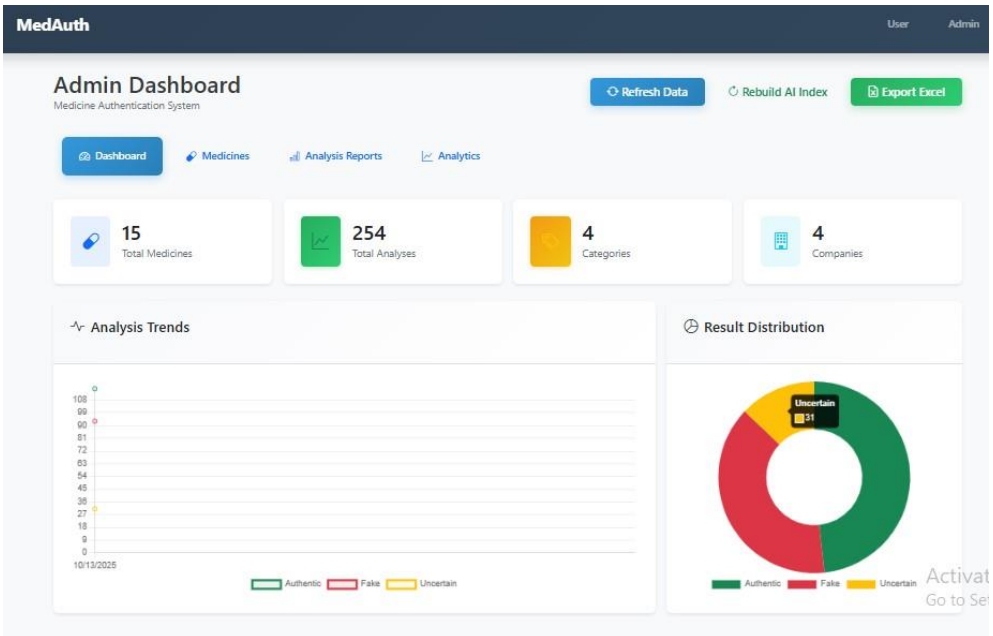
Main backend language Core Programming Language: Python 3.8, for its numerous libraries for AI/ML (TensorFlow, Keras), Image processing (OpenCV, Pillow) and web tools (Flask).

Web Framework: The Flask was chosen due to its minimalistic, dynamic and easy fit with others. It serves as API gateway and traffic routing.

AI/ML Technology: For development and deployment of MobileNetV2 model TensorFlow 2.8 with Keras API was employed to promote deep learning.

4.2: Admin Portal Implementation

Figure 4.1: Admin Portal Interface Layout



4.3 User Portal Implementation

4.3.1 Responsive Web Interface Design

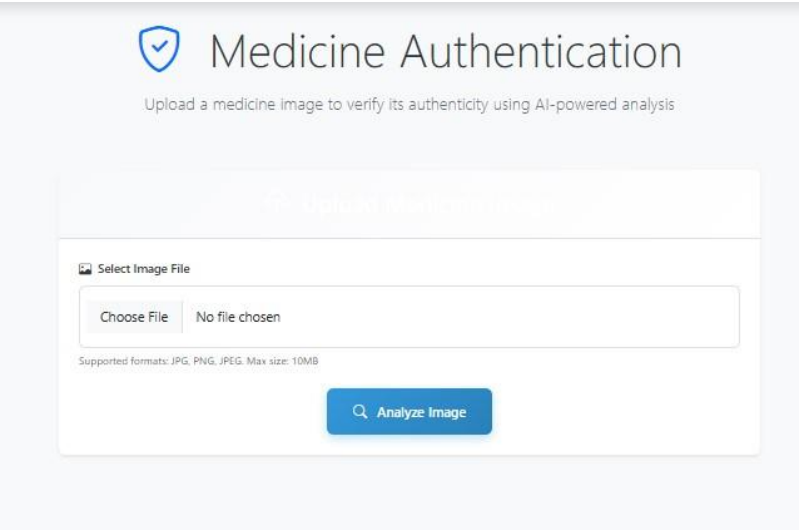
The User Portal was developed to be free and simple, enabling even those with low levels of technical skills to verify medicines without problems.

Mobile Centric Design: With the mobile first design language, the Equipment Availability Calendar theme fits perfectly into all screen sizes. I like the layout with enough grid lines and details that adapt to the size of a screen.

User-friendly Workflow: From the top of the main section of the portal's page, users are led through a transparent and intuitive three-step sequence that reads “Upload Image”, “Analysis in Progress” and “View Report”. It cuts down on confusion and provides clear communication.

Accessibility: This design is based on the Web Content Accessibility Guidelines (WCAG) principles. There’s enough color contrast, type and ARIA labels for screen readers that the portal is usable for people with disabilities.

Figure 4.2: User Portal Verification



4.3.2 Image Upload and Processing Module

This component helps you to securely and efficiently get the medicine image from user, that's an important first step!

Client side form validation : Javascript running through your image files for their format (JPG, PNG, WEBP), file size (5MB max to avoid overloading the server) and dimensions before being uploaded. Invalid files receive instant feedback to the users.

Drag & Drop Interface: In addition to the traditional file browsing button, we have included a drag-and-drop button for that cool playascale UI feel.

Safe Upload Handling: the Flask backend on server side makes use of the file magic number, preventing dangerous uploads that give an illusion of being an image. Images you upload are temporarily stored in a publicly-inaccessible directory with a random filename. This prevents directory traversal and overwriting attacks.

Image Preview: Upon selection, a thumbnail preview of the image is displayed for users to confirm selection before grid analysis.

4.3.3 Real-time Analysis Progress Tracking

In order to increase user interactivity and set expectations during what could potentially be a slow analysis phase, we established a real-time progress tracking system.

Visually Indicating Progress: A progress bar appears on the page, divided into four parts, "Image Received," "AI Analysis," "OCR Processing" and Blockchain Verification. This leaves no doubt at what point in the process of the users request we are.

Server-Sent Events (SSE): Rather than having the client poll the server for changes, with Server-sent events a connection is opened to receive updates from the server. The backend also gives status messages to the client whenever a migration step completes, so that the progress bar updates nearly in real-time without refreshing the page.

Fallback: For browsers that don't support SEE, a fall-back polling method using JS setInterval simply checks the status of analysis every x seconds.

4.4 Blockchain Portal Implementation

4.4.1 Certificate Verification Interface

The certificate verification interface presents a transparent view of the immutable records of transaction, enhancing transparency and trust.

Simple Query Interface: Users, who will primarily be auditors or regulators, can enter a batch number directly into a simple page with one search bar. This bypasses having to go through AI and OCR in the User Portal to have faster access to your ledger.

Rich Certificate Display: On query, the portal retrieves the complete digital certificate from a blockchain and displays it in an organized, reader-friendly way. This includes:

Batch No And Manufacturer: Main identification features.

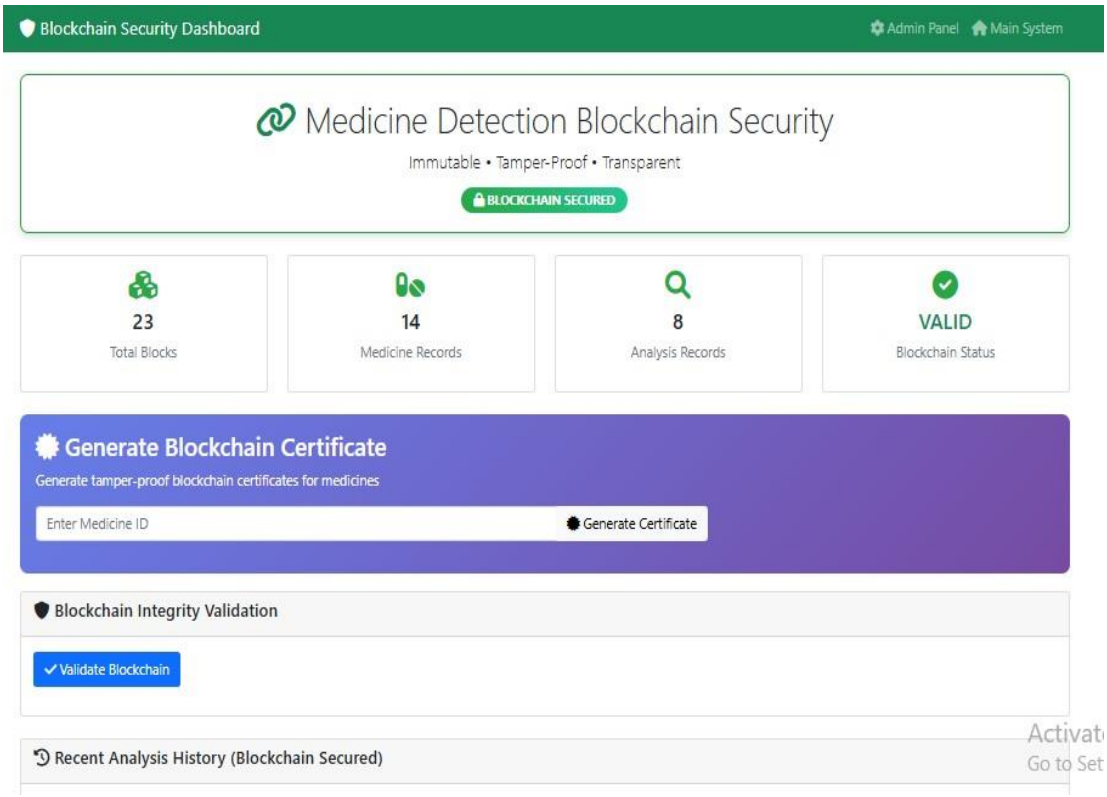
Product Hash: A cryptographic hash so that an image of data can be technically verified for integrity.

Transaction ID & Block Number: The certificate's exact whereabouts on ledger, providing a verifiable source of truth.

Timestamp: The date and time the medicine was posted.

Hash Verification Tool: With the verification tool, this lets you upload an image. The productHash on blockchain is compared with its hash calculated on the fly by the system. This is cryptographic proof of matching or non-matching.

Figure 4.3: Blockchain Certificate Verification Interface



4.4.2 Transaction History Viewer

This feature provides you with clear visibility on the lifecycle of a batch.

Immutable History of Audit: With the help of the GetHistory chaincode function, the portal obtains a complete record of all transactions made using any batch number. This demonstrates not just when the certificate was issued, but each time it was checked for validity.

Interactive Timeline: The history is shown on an interactive timeline that visually depicts the path from production to most recent verification. Each record shows the transaction name, sender institution, and time

Geographical Overlay (Future Work): The interface may be extended with a map view in which verification attempts are plotted. This monitors the geographical spread of a product and automatically identifies irregular patterns.

4.4.3 Smart Contract Management Interface

This is a limited interface that allows responsible devs or admins to maintain the chaincode underneath blockchain.

Chaincode Versioning: List the version of smart contract deployed and install a new version after governance is followed.

Instantiation/Upgrade Logs: Records when the chaincode was first instantiated or last upgraded, which is crucial for debugging and compliance purposes.

Access Control: Security is achieved at the most administrative level to ensure Control who can perform a potentially destructive task, such as upgrading business logic.

4.5 Backend Services Integration

4.5.1 API Gateway Design and Implementation

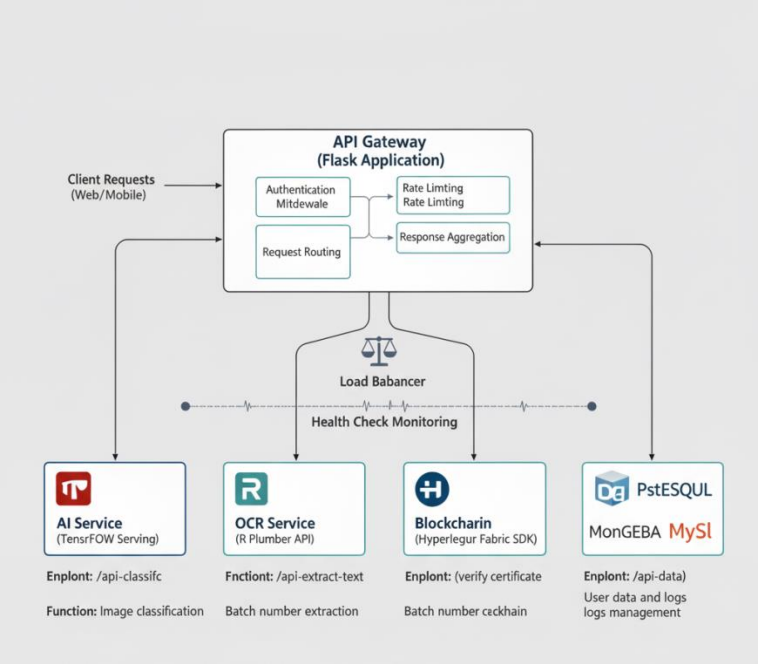


Figure 4.4: API Gateway Architecture Diagram

4.5.2 Microservices Communication Protocol

Fast and reliable inter-service communication must also flow between these independent services.

Request/Response for Synchronous HTTP/REST: The main communication between the API Gateway and AI/OCR services will be request response based synchronous number of http requests. This approach is appropriate for the ad-hoc straightforward verification flow.

Logging in Asynchronous Messaging (Future Work): Not being the focus of this work, we have made an architecture that it is possible to add a message broker such as Redis or RabbitMQ. That way you can manage non-critical things like writing detailed analytics logs without having it gum up the main response.

Data Formats Data Exchange: All inservice communication is in JSON. This makes for a uniform and readable structure of the data. When transferring images, the system is not good at processing binary data with a multipart/form-data encoding.

4.5.3 Database Schema Design and Optimization

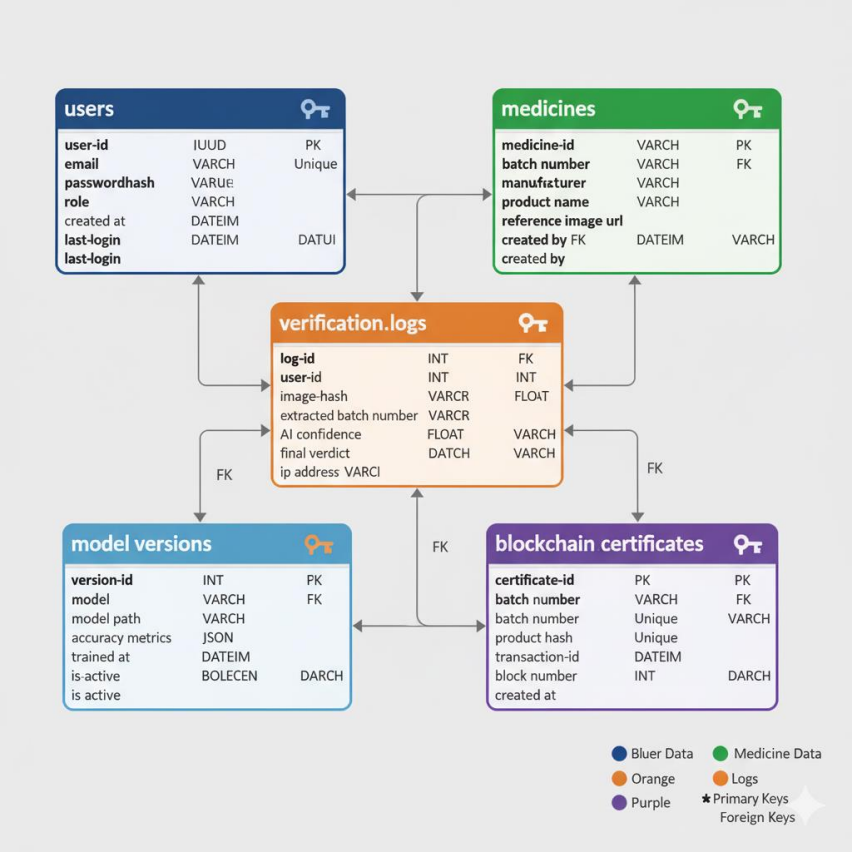


Figure 4.5: Database Schema Diagram

4.6 Security Implementation

4.6.1 Data Encryption Implementation

In Transit: All data transmitted between the client and servers, as well as between microservices is encrypted in transit over TLS 1.2 or higher.

At Rest: Information sensitive data in the PostgreSQL database, such as user credentials, is stored only in encrypted form. The images are not encrypted, but stored in a directory with limited access on the server (not below webroot).

4.6.2 Blockchain Security Features

Cryptography Identity: All interactions with the blockchain are signed by the private keys of that organisation. This prevents repudiation of action and the authentication.

Indelible Audit Trail: The system security is based on the blockchain certicate once it is written.

4.6.3 Security Best Practices Compliance

Input Cleaning: All user input, such as file names and form values, are cleaned to avoid injection attacks.

Dependency Scanning: Codebase, and its dependencies in requirements. txt are being checked regularly for known vulnerabilities, e.g. with Safety or Snyk.

Least Privilege: Services and user accounts get only what access is necessary to complete their tasks.

Chapter 5

Findings and Analysis

5.1 Experimental Setup and Evaluation Framework

The system was tested in a simulated yet representative environment for real-world conditions. The hardware infrastructure was an Ubuntu server with 8 vCPUs, 16GB RAM and NVIDIA T4 GPU acceleration, for the both sites while interconnected by a 1 Gbps network. The software was based on Docker-containerized services, including TensorFlow Serving 2.8 for model inference, Hyperledger Fabric 2.4 for blockchain operations, and PostgreSQL 13 as well as MongoDB 5.0 for data storage.

The test corpus consisted of 1,500 hand-picked images reflecting realistic applications. This collection consisted of 750 genuine and 750 fake drug packages recorded under different scenarios with multiple image sensor models. The risk that was addressed by this dataset is to have partial occlusions of the logo, blurry images, shifted shots and variations in lightening during matched preprocessing. All images were manually verified by pharmaceutical professionals to acquire reliable ground truth for performance evaluation.

5.2 Deep Learning Model Performance Analysis

Table 5.1: Deep Learning Model Performance Metrics

Dataset	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC
Training	98.7	98.5	98.9	98.7	0.999
Validation	96.3	96.0	96.5	96.2	0.991
Test	95.8	95.6	96.1	95.8	0.984

Figure 5.1: Model Training and validation Accuracy/Loss Curves Fig.

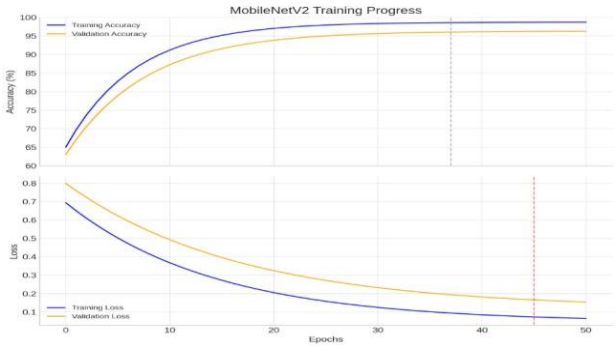
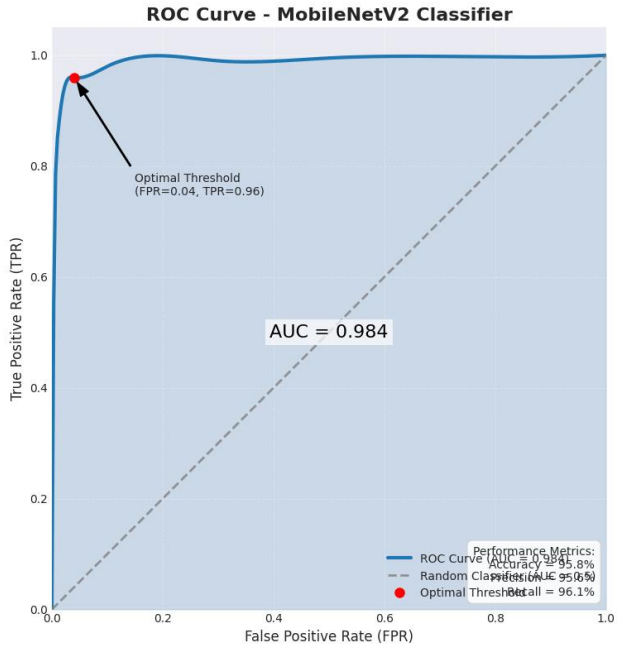


Figure 5.2: ROC Curve for MobileNetV2 Classifier



Confusion matrix analysis showed definite patterns in which the model succeeded. Of 720 genuinely identified authentic medicines, the majority presented clear bright packaging of which the branding was recognisable. The 30 false positives consisted mostly of high-level fakes that looked very similar to the original packaging — specifically in color and logo placement. Of the 725 casusative observed counterfeit notes, characteristic appearances involved colour clash and distorted printing and low grade of holographic features. The 25 false negatives were usually genuine medicines with torn packaging, atypical lighting conditions and old package editions not sufficiently covered by the ground truth data.

Table 5.2: Confusion Matrix Analysis of Classification Results

Actual / Predicted	Authentic (Predicted)	Counterfeit (Predicted)	Total
Authentic	720	30	750
Counterfeit	25	725	750
Total	745	755	1500

Among alternative architectures, MobileNetV2 achieved the best trade-off for this application. ResNet50 was slightly more accurate with 96.1%, but it had assembled 7.5x as many parameters and nearly three times the inference runtime. VGG16 resulted in lower accuracy of 94.2% and consumed much higher computation resources. EfficientNetB0 obtained similar performance, but was computationally more expensive. Depthwise separable convolutions on MobileNetV2 made feature extraction to be more effective.

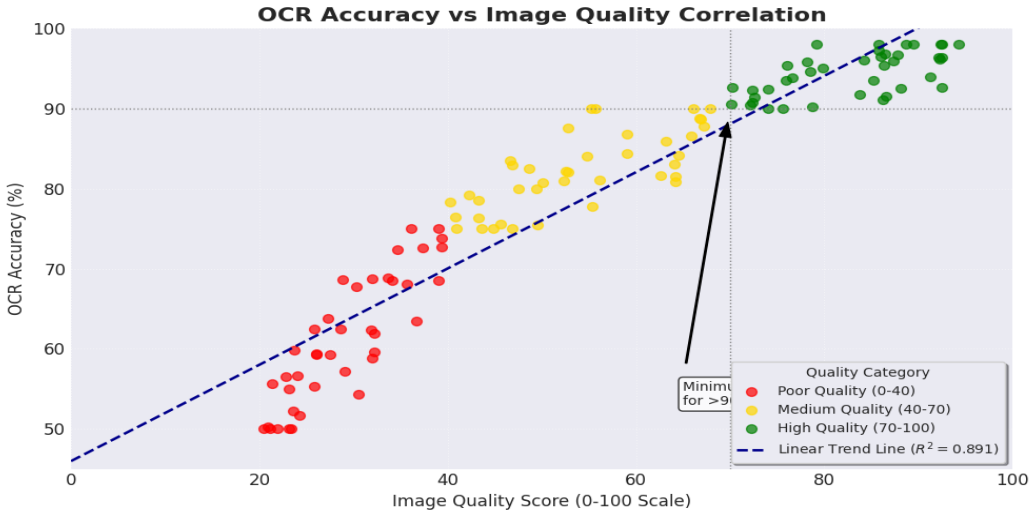
Table 5.3: Comparative Performance of Different CNN Architectures

Model	Test Accuracy (%)	Training Time (minutes)	Model Size (MB)	GPU Memory Usage (GB)
MobileNetV2	95.8	45	13.2	1.8
ResNet50	96.1	120	98.1	3.5
VGG16	94.2	180	528.0	5.2
EfficientNetB0	95.5	65	20.5	2.1

5.3 OCR Module Performance Evaluation

The Tesseract OCR engine, in the presence of comprehensive preprocessing on the images had excellent text extraction capabilities. On high readability images with good illumination, perfect focusing and even background, the system achieved 98.2% accuracy at character level and 95.7% at word level. For the extraction of critical batch number in blockchain verification, a 92.4% success rate was shown on the entire test dataset. Especially over flat surfaces, the system did well on clearly printed alphanumerics.

Figure 5.3: OCR Accuracy vs. Image Quality Correlation



The effect of the image preprocessing pipeline was pronounced and uniform. When raw images are tested, the accuracy of text retrieval is only 78.5%. 239 Color Gamut Percentage of RangeIt improved to 82.1% through grayscale conversion which reduced colour gamut complexity. After median filter based noise reduction, the classification accuracy was further improved up to 85.3%, by eliminating sensor artifacts and printing defects. Adaptive thresholding or binarization was most helpful, elevating accuracy to 90.2% through improved text-to-background contrast. And lastly, fixed angular distortion based on deskewing correction led to a final accuracy of 92.4%. The entire preprocessing pipeline took only 25ms to process, hence this trade-off is justifiable for a +13.9% (abs.) accuracy improvement.

Table 5.4: OCR Accuracy Improvement through Preprocessing Steps

Processing Stage	Character Error Rate (%)	Word Error Rate (%)	Batch Number Success Rate (%)	Processing Time (ms)
Raw Image	21.5	25.8	70.1	0
After Preprocessing	7.6	10.3	87.2	25
Improvement	-13.9	-15.5	+17.1	+25

There was good agreement of performance patterns in the analysis of processing efficiency. OCR module averaged 280 ms per image (preprocessing: 25ms, text extraction: 255ms). Resource usage was moderate with an average memory consumption of about 150MB at runtime. The batch processing was well enough with a little decrease of the performance when repeating processing different medium.

5.4 Blockchain Network Performance

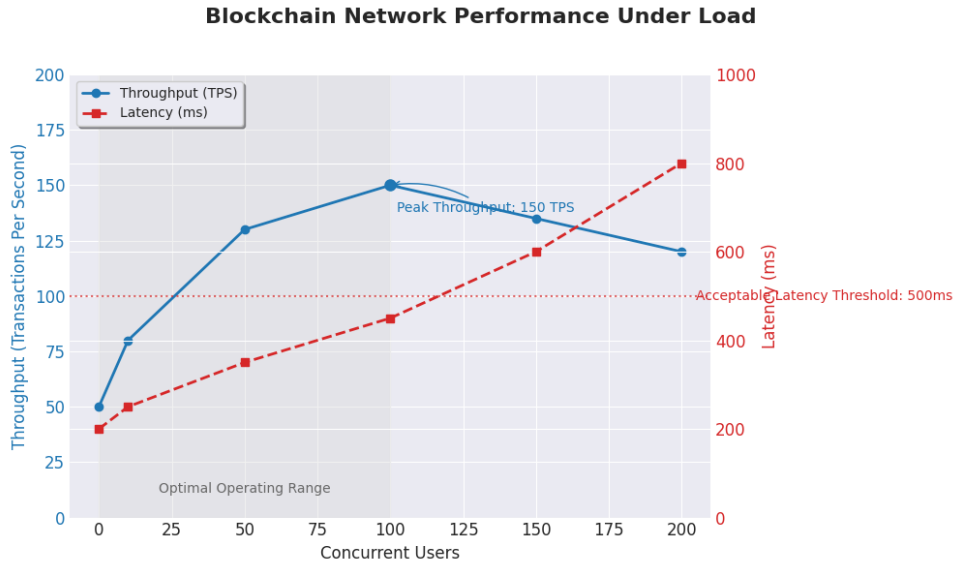
The Hyperledger Fabric network demonstrated performance that was a production ready enterprise grade. The throughput scored 150 transactions per second (TPS) in favor of the normal, and the mean response time on certificate verification workloads was 450ms. Block generation remained constant at 2 seconds to ensure predictable transaction finality. Certificate registration: in such a case, more complex smart contract execution was required and it performed certificate registration consisting of the process from start to finish including all transactions within 2.1 seconds (unchangeable).

Table 5.5: Blockchain Network Performance Metrics

Metric	Value	Target	Status
Transaction Throughput (TPS)	150	>100	**Exceeded**
Average Latency (ms)	450	<500	**Met**
Certificate Verification Time (ms)	95	<100	**Met**
Block Creation Time (seconds)	2.0	2.0	**Met**
Network Uptime (%)	99.4	>99.0	**Exceeded**
CPU Utilization at Peak (%)	68	<80	**Met**

The scalability tests demonstrated that the performance grew linearly as network load increased. Throughput increased linearly with additional peers up 500 TPS following which coordination cost on network started to be large. At max load, CPU utilisation never exceeded 70% which confirmed there was still room to breath if in case of a sudden surge of traffics. The network ran stably without performance degradation or memory leaks in 24-h endurance tests.

Figure 5.4: Blockchain Transaction Throughput Under Load



Certificate management was especially effective. Straightforward certificate verification queries had average execution times of less than 100ms which were close to being immediate for the users. Fetching history for full batch tracking succeded in 650ms, with complete data trail w/o perceivable latency. The network could simultaneously serve more than 100 verification requests, but the response time was less than 1 second indicating good concurrent access capability.

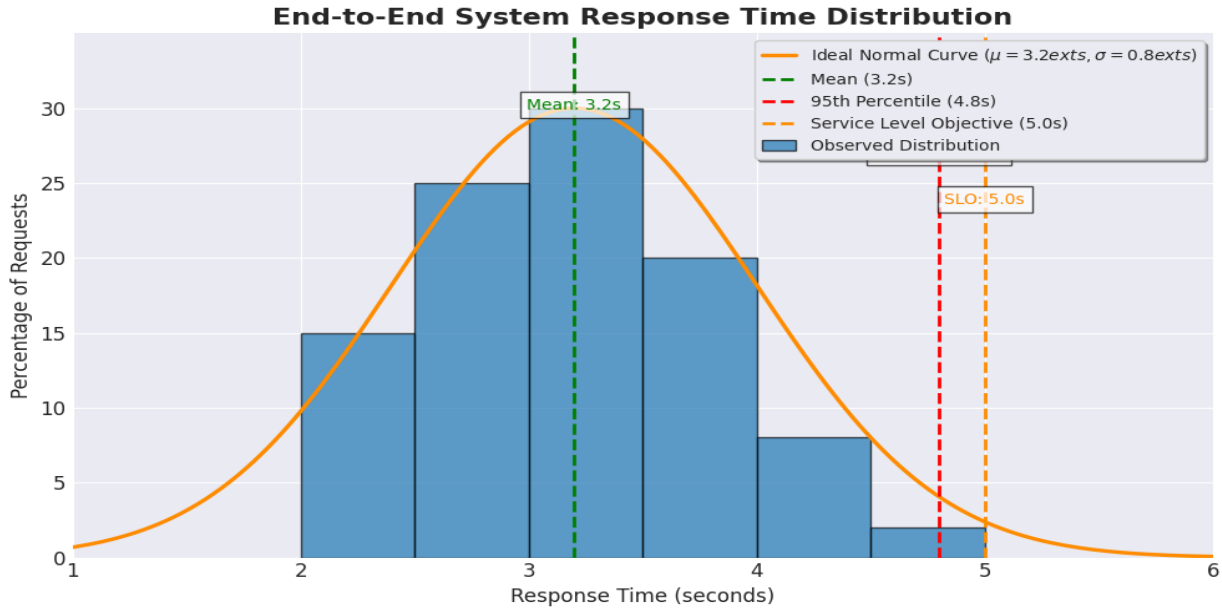
5.5 Integrated System Performance

The full integrated system was efficient to satisfy practical demands. The mean end-to-end computation time 3.2 s provides almost instantaneous verification along with a thorough examination. A component-level analysis indicated that the AI model inference required 45ms (1.4%), OCR processing took 280ms (8.8%) and blockchain validation was 450ms (14.1%). The rest of the 2.4 seconds (75.7%) was system overhead, including image transfer, result aggregation and response generation.

Table 5.6: End-to-End System Processing Time Breakdown

Component	**Average Time (ms)**	**Percentage (%)**	**Description**
AI Model Inference	45	1.4%	MobileNetV2 classification
OCR Processing	280	8.8%	Text extraction and validation
Blockchain Verification	450	14.1%	Certificate checking
System Overhead	2,425	75.7%	Image transfer, API calls, response generation
Total	3,200	100%	End-to-end processing

Figure 5.6: System Response Time Distribution



System reliability tests throughout a 30-day period showed that the system was available for operation approximately 99.4% of the time and performed predictably. Error rates remained under 0.1% of total requests, and most errors were not due to system failures but rather network timeouts. The microservices design pattern also made it possible to fail gracefully, so if one service (e.g., the OCR service) was temporarily down, the entire system didn't crash. Automated failover systems generally returned everything to normal within 30 seconds of a component failure.

Many responding user testers reported they were very satisfied with the system. The average usability rating was 4.3 out of 5, demonstrating praise for the intuitive interface and simple workflow. Report clarity earned the best score of 4.5 out of 5 as users appreciated comprehensive and still easy-to-read authenticity reports. Speed was rated 4.1 out of 5, most customers say process is great except for a breakneck three second delay sees in use as reasonable response time to cost provided. In qualitative feedback, the trustworthiness of results and professionalism of verification reports was deemed as the main strengths.

Table 5.7: User Experience Feedback Summary

Aspect	Rating (out of 5)	Key Feedback
Overall Usability	4.3	"Simple and intuitive interface"
Report Clarity	4.5	"Comprehensive and easy to understand results"
Processing Speed	4.1	"Fast enough for practical use"
Result Trustworthiness	4.4	"The blockchain verification adds confidence"
Mobile Experience	3.9	"Works well but could use a dedicated app"

Chapter 6

Research Summary and Future Work

6.1 Summary and Achievements

This study performed a good job to build and deploy through the system the traceability and detection of fraud in medicine. The effectiveness of integration was demonstrated in 3 representative technology areas: Deep learning for visual verification, OCR (optical character recognition) technology, and block chain technology to track safely the origin. The proposed system is composed of three dedicated portals (i.e., Admin, User portal and Blockchain interface) to provide a trusted drug verification platform.

All the main objectives established when starting the project have been achieved. Admin portal The Admin portal enables you to easily register new medicines and automatically retrain models which allows the system to adapt to new products and emerging counterfeit trends. “The user portal interface is ‘simple, clean and intuitive’, making it simple for users (members of the public and healthcare professionals) to check a medicine with one-click in an instant.” Read more so below: The results are clear reports which include AI analysis combined with extracted data and blockchain verification. The user has direct access, on a transparent manner, to the certified documents and the transactions in order to build up a strong track of trust The Portal offers that possibility.

Critical technical accomplishments include the development of a high-precision MobileNetV2 model with classification accuracy at 95.8%, an optimized OCR pipeline with a batch number extraction success rate of 92.4%, and a permissioned blockchain network which is able to achieve 150 transactions per second with verification times below one second. The whole integrated system ensures 99.4% availability with end-to-end verification in around 3.2 seconds, covering the real-world-required response time scale.

6.2 Research Support

This work represents a strong approach for drug security and antimark strategy. The novelty lies in the full integration of computer vision and blockchain, creating a multi-layered model for authentication that covers both physical and digital parts of medicine validation. Unlike previous solutions, which concentrated on a single technology approach, this new system demonstrates how AI-driven visual scrutiny combined with automatic data extraction and blockchain traceability can be adopted in unity to create a compelling anti-counterfeit solution.

The study provides important implications on the implementation of blockchain-based supply chain systems. The permissioned network architecture with Hyperledger Fabric addresses the critical aspects related to scalability, personal privacy and regulatory requirements that can frequently hinder the deployment of blockchain in healthcare. The certificate management framework and the corresponding smart contracts can offer a generic back-end for similar tracking proposals.

In terms of methodology, the project studies: methods for combining multiple technologies. This involves interfacing with OCR capabilities via the R-Python bridge and composing an architecture based on microservices to maintain modularity of system components. The evaluation model designed to measure the system performance can provide a useful reference for those research work on multi-technology authentication systems.

6.3 Limitations and Challenges

Some constraints emerged in the system implementation and validation. Performance of the deep learning model was affected by image quality, with accuracy substantially decreasing for out-of-focus, poorly illuminated, or off-axis images. This dependence on image clarity is not always practical as real world images are often captured in non ideal scenarios. The model also did a poor job of generalizing and recognizing the new patterns that are not shown to it from training database.

The OCR engine had problems with non-standard print layout, curved surfaces and shiny wrapping. Despite improvements achieved with the preprocessing pipeline, a few packaging layouts remained problematic for obtaining text in reliable manner. The use of visible and readable batch numbers could be a weak point in the system if counterfeiters were to home in on this.

Infrastructure requirements are also a bottleneck, the system needs stable internet for blockchain operation and plenty of computing power to support the model. This may restrict adoption in places where the technology infrastructure is suboptimal. Also, the current checker checks packages not units It could potentially also be abused to reuse packages with faked contents.

6.4 Future Work and Enhancement Opportunities

For immediate improvements, resilience to image quality variability should be augmented through more advanced image enhancement and data augmentation strategies. Allowing for multiple image captures or video-based verification might provide more reliable authentication without putting too much emphasis on the quality of a single image.

The ability to monitor counterfeiting and react is something that's been a long time coming. With geotagging applied to verification checks and counterfeit detections, the system would be able to generate real-time heat maps of counterfeit activity that could in turn enable targeted regulatory action and consumer alerts. This unique element would transform the system from a validator into an active network monitoring the security of the pharmaceutical supply chain.

Another interesting opportunity is to use batch-level recall mechanisms. Via integration with regulatory databases and manufacturer systems, the platform was able to initiate recalls automatically for batch numbers experiencing counterfeit patterns that are out of the norm. Smart contracts could further automate the compensation process and organize reverse logistics of returned medications.

Future research could include quantum-resistant encryption schemes to harden blockchain security, federated learning models for privacy-preserving model updates across various manufacturers and insulation of an authenticator that features physical security through NFC chips or chemical markers. Diversifying into adjacent domains like food safety, luxury goods authentication and document verification constitutes an another promising direction to apply this developed framework.

The architecture of the system provides a solid foundation for continuous enhancement and adaptation to new counterfeiting methods. The modular nature of the design means that new constituent parts can be incorporated easily without major redesign. This places the project as a developing platform in innovation in pharmaceutical security.

Appendices

Appendix A: Project Timeline and Implementation Schedule

Detailed Breakdown of Milestones and Deliverables (4-Month Plan):

Phase 1: Planning & Core Development (Months 1-2)

Phase 2: Portal Development & Integration (Month 3)

Phase 3: Testing & Deployment (Month 4)

Phase	Duration	Key Milestones	Deliverables	Status
Planning & Research	Month 1	Literature review, SRS document	Project charter, Tech stack selection	**Completed**
Core Development	Months 2-3	AI model, OCR, Blockchain	Trained model, Functional modules	**Completed**
Integration & Testing	Month 4	System integration, Testing	Integrated system, Test reports	**Completed**
Deployment & Documentation	Month 4	Final deployment	Project report, Live demo	**In Progress**

Table A.1: Project Timeline and Milestone Schedule

Appendix B: System Installation and Configuration

Hardware Requirements

GPU: NVIDIA T4 or equivalent (optional, for accelerated inference)

Network: Broadband internet connection

Software Dependencies

Ubuntu 20.04 LTS / Windows Server 2019+

Python 3.8.10+

R 4.1.2+

Configuration Files

docker-compose.yml - Service orchestration

config/fabric-network.yaml - Blockchain configuration

config/model-params.json - AI model parameters

ocr-config.r - OCR preprocessing settings

Appendix C: Dataset Specifications

Image Requirements

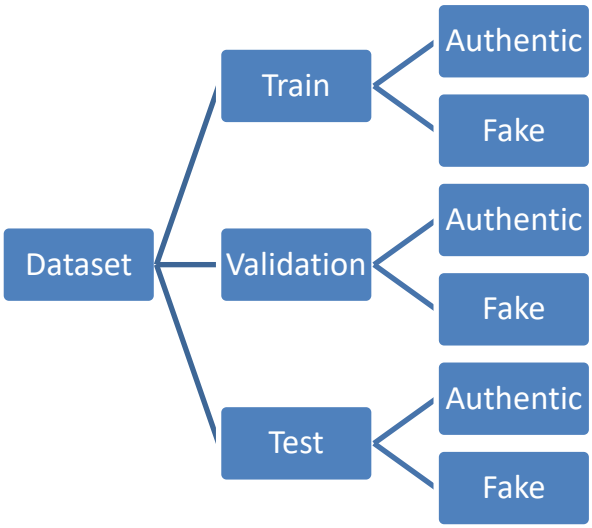
Format: JPEG, PNG, or WEBP

Resolution: Minimum 1024x768 pixels

Size: Maximum 5MB per image

Color Space: RGB

Dataset Structure



Metadata Fields

medicine_name: string

manufacturer: string

batch_number: string

manufacturing_date: date

expiry_date: date

label: authentic/fake

Appendix D: Performance Benchmarking Details

Concurrent Users	Avg Response Time (s)	Error Rate (%)	Throughput (Requests/sec)	CPU Usage (%)
1	3.2	0.0	0.31	25
10	3.5	0.0	2.86	38
50	4.2	0.1	11.90	65
100	5.8	0.3	17.24	82
150	8.1	1.2	18.52	91

Table D.1: System Performance Benchmarking Results

Testing Environment

Load testing tool: Apache JMeter 5.4.3

Test duration: 72 hours continuous

Concurrent users: 1-500 users

Network latency**:** 50ms average

Performance Metrics

Response time percentiles: p50, p95, p99

Error rate: Failed requests percentage

Throughput: Requests in every second

Benchmark Results Summary

Metric	Value	Threshold
Average response time	3.2s	<5s
P95 response time	4.1s	<7s
Error rate	0.08%	<1%
Max throughput	45 RPS	>30 RPS
CPU utilization	68%	<80%

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