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AI Predictive Analytics for Verifying Pharmaceutical Authenticity and Combating Drug Counterfeiting

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Abstract:

A significant worry in recent years has been the counterfeiting of medicines. The distribution and manufacture of fake or falsified drugs are both criminal and harmful to the public's health. The severity of this issue differs significantly from one country to another, primarily due to variations in the adherence to national regulations and processes. Thus, preventing the sale of fake drugs has become an urgent matter, particularly in poor and developing nations. The study presents a new multi-layered validation structure for pharmaceutical authenticity verification that uses Generative Adversarial Networks (GANs), Convolutional Neural Networks (CNNs) and blockchain technology for artificial intelligence predictive analytics. The goal is to tackle the widespread problem of counterfeit drugs. Using GANs to sift through past data, the suggested strategy improves the detection of minor package variations by identifying trends and traits linked to counterfeit drugs. Using the GAN-generated enhanced dataset, a CNN is trained to accurately and specifically categorize drug packaging.Further, the framework uses blockchain technology to provide trustworthy and transparent recordkeeping of drugs in realtime as they move through the supply chain. Increased patient safety directly results from our system's thorough audit trail, which solves the problems of fake medications and regulatory compliance. The suggested approach reduces counterfeit dangers and provides a scalable paradigm for other industries to use when dealing with similar authenticity verification issues, which means it can find more uses in safety-critical fields. The success of the multi-layered validation structure model is evaluated using performance metrics such as accuracy, recall, and F1-score. It achieves a fantastic accuracy rate of over 95%.

Keywords: Convolutional Neural Networks, Drug Counterfeiting, Performance Metrics.

1. INTRODUCTION

Pharmaceutical businesses prioritize distribution maintenance during repackaging or relabeling to optimize distribution routes and safeguard patients from errors [1]. Pharmacy managers, wholesale distributors, and others are involved in the pharmaceutical supply chain. Pharmaceutics supply chain services include clinical research and wholesale distribution [15]. Private corporations, government agencies, and consumers scrutinize the healthcare and pharmaceutical industries, making them challenging to manage [18]. This complexity complicates the reduction of counterfeit pharmaceuticals and causes cold-chain shipping, which raises prescription drug prices, causes supply shortages, and worsens medication pricing [3]. Pharmaceutical products labelled "counterfeit pharmaceuticals" are made to deceive clients by using fake names and labels. In addition, counterfeit pharmaceuticals may have inappropriate formulations, such as inadequate API, impurities, or repackaged old medication, and poor manufacturing standards [22]. The quantity of medicines and technological advances that have led to the development of new pharmaceuticals under different brands are increasing the potential of drug counterfeiting.To protect patient health, several healthcare institutions are using cutting-edge technologies to avoid pharmaceutical counterfeiting [16]. Many markets and our daily lives have changed due to recent AI advances. AI could speed up and improve scientific data processing and publication [4]. The traceability of drugs is crucial to these efforts. The pharmaceutical sector must establish a scalable, computerized system to detect and track prescription drugs to comply with the Drug Supply Chain Security Act [5]. Creating a national standard for tracking and tracing drugs is the biggest issue. Traditional counterfeiting prevention measures like digital tracking or physical inspection fail. They cannot provide tamper-proof real-time verification or keep up with evolving counterfeiting methods.

This study offers a multi-tiered pharmaceutical authenticity verification system using blockchain and artificial intelligence like GANs and CNNs [14]. The purpose of this system is to overcome these problems. The hybrid approach uses immutable recordkeeping and predictive analytics to build a robust verification system to identify counterfeit medications. It stands out from other models with this characteristic. By studying historical data, GANs can create synthetic patterns that resemble counterfeits [17]. The CNN's capacity to detect even minute irregularities improves, and the dataset grows [12]. Blockchain technology provides a decentralized, tamper-resistant record for tracking medications from production to sale, increasing supply chain security [2] [7]. The framework uses cutting-edge AI algorithms to improve medication verification accuracy.

Along with tackling pharmaceutical logistics' transparency and traceability challenges [23]. This methods use image-based verification and secure ledger technologies to tackle global and local drug counterfeiting. Scalability between pharmaceutical categories and locations is also possible. This study examines the system's architecture, implementation, and performance to prove its efficacy in real-world situations.

The main contribution of the article include:

1. The research introduces a novel multi-layered validation framework for pharmaceutical authenticity verification using blockchain technology, GANs, and CNNs.
2. GANs filter past data to discover phoney pharmaceutical trends and characteristics, improving the detection of modest package modifications. Using a GAN-generated augmented dataset, a CNN classifies medication packaging accurately.
3. The solution also uses blockchain technology to provide reliable real-time drug records across the supply chain. Multi-layered validation measures model performance using F1-score, recall, accuracy, and precision.

2. LITERATURE SURVEY

Ullagaddi, [9] delves into the future of digital transformation of quality management systems (DT-QMS) and its trends and opportunities. Blockchain technology to ensure data integrity and transparency in the supply chain, Internet of Things devices to track quality in real time and perform predictive maintenance, big data analytics and machine learning to improve quality, and working with regulators to establish digital quality management standards are some of these trends and possibilities [6, 8]. The report recommends a comprehensive, strategic, and collaborative strategy for the pharmaceutical industry to profit from digital transformation, including technology, people, processes, and partnerships.Májovský et al., [19] examined how well AI language models can spoof medical records. Using the GPT-3 language model, this study created a fictional neurosurgery paper. This study demonstrated ChatGPT's proof-of-concept effectiveness. OpenAI's GPT-3 is a massive language model that mimics human speech in response to user input using deep learning. The model learned from a large online text corpus and can write well in many languages and topics. The study found that the artificial intelligence language model can imitate a scientific publication's style, grammar, and vocabulary to create a convincingly fraudulent piece. Chen et al., [11] introduce ClinAIOps, "clinical artificialintelligence operations." This paradigm combines therapeutic monitoring with AI research. ClinAIOps has three feedback loops: one for the patient to use AI outputs to change their therapy, one for the clinician to track their success, and one for the AI developer to get ongoing feedback from both. Each feedback loop is named after an AI feature. They were analyzing the use of ClinAIOps to treat hypertension, diabetes, and Parkinson's disease to demonstrate its main obstacles and potential benefits. ClinAIOps may enhance patient outcomes by allowing more frequent and precise health evaluations and faster treatment changes [10].

Dogheim & Hussain, [20] illuminate the complex function of predictive models and intelligent warnings in preventive medicine. Risk stratification begins with predictive algorithms that analyze massive amounts of genetic, clinical, and demographic data to find trends. Second, predictive models can recommend preventative steps by merging historical data with present risk profiles. Integrating predictive algorithms and intelligent warnings optimizes resource allocation, among other benefits. Healthcare systems can maximize preventative treatment by identifying and focusing on high-risk individuals. Finally, prediction models enable prevention evaluation and improvement. Comparing predictions with actual results helps improve models and actions. It allows these models to produce more accurate projections and implement preventative tactics.Singh& Kaunert, [13] introduce permissioned blockchain technology with AI (AI-BC) for user-centric health data sharing. A channel construction method protects users' privacy, and the membership service improves identity management. Privacy, confidentiality, and self-sovereign data ownership drive blockchain technology use in health record storage and transfer systems. To use data for informed decision-making and better patient outcomes while maintaining patient privacy and data security, healthcare analytics requires secure data sharing and collaboration. This chapter showed that securely transferring and analyzing sensitive healthcare data requires a combination of technology solutions, legal frameworks, and best practices.

Sayem et al., [21] examine how new technologies like AI provide more efficient ways to fight healthcare fraud. Speech biometrics and patterned voice analysis are AI-powered tools that identify fraudulent conduct more efficiently and accurately than earlier methods. This study quantitatively reviews AI potential to reduce healthcare risks. Data-centricity, which has existed since large-scale tagged Medicare databases, helps healthcare providers speed policyholder payouts and recordkeeping. Current research suggests that AI-based fraud-reduction tactics could impact the healthcare industry. By improving and automating fraud detection, the healthcare business may be able to secure patient data, finances, and public trust. AI may also help prevent healthcare fraud, making the system more effective and safe.

3. SYSTEM METHODOLOGY

3.1. Overview of the Proposed Model

A multi-layered verification flow structure in Figure 1 is a strategy that utilizes GANs, CNNs, and Blockchain Technology. This framework is an all-encompassing approach to verifying the validity of pharmaceutical products. Using data, the GAN layer analyzes and develops patterns, the CNN layer performs visual verification, and the blockchain layer monitors the supply chain's integrity using blockchain technology. Each of these three layers constitutes the entirety of the process. The pharmaceutical goods are documented securely throughout the supply chain, and the identification of medication counterfeiting is accomplished with a high degree of accuracy through an integrated workflow. GAN Layer uses include data analysis and pattern development. Adding synthetic counterfeit medicine patterns from historical data to the training dataset improves the artificial intelligence predictive model's capacity to recognize counterfeit packaging. Include real and fake drug photos in the GAN model. Include all historical data. GANs can evaluate the dataset to generate new synthetic counterfeit images replicating packaging variations.

In a GAN design, the Generator (G) learns to create more convincing counterfeit patterns, while the Discriminator (D) determines if the picture is accurate. This layer trains the CNN model with the latest dataset.CNN Layer is crucial to fighting pharmaceutical counterfeiting and visually verifying drug purity. Use Convolutional Neural Networks to verify pharmaceutical packaging's appearance. We feed the CNN model medication box photos to train it. Convolutional neural networks (CNNs) extract picture characteristics using convolutional and pooling layers. Physical features like holographic seals, barcode patterns, and texture can distinguish genuine from counterfeit medications. The final classification by fully linked layers yields a probability score indicating whether the medicine is legitimate or counterfeit.

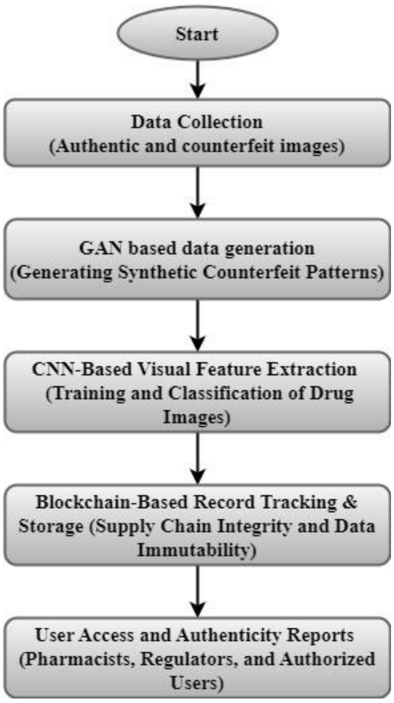

Fig. 1: Flow Structure of the Proposed Model

Next, the Blockchain Layer will develop Supply Chain Integrity Tracking to make the pharmaceutical supply chain visible, traceable, and safe. The blockchain stores each drug batch's origin, manufacturing date, and validity status. The blockchain gives each drug batch a unique ID. We track the drug's status and location as it moves through the supply chain from manufacturer to distributor to store.

To prevent manipulation, all transactions are double-verified using cryptographic signatures and consensus processes. Distributed ledger technology allows regulatory agencies and pharmacists to verify drug validity and track its location in real-time. This multi-tiered system's thorough verification and traceability reduces the likelihood of counterfeit medications entering the supply chain.

3.2. GAN Model

The Generator (G) and Discriminator (D) are the Generative Adversarial Network's main components. Minimax games involve these two components. In this scenario, the Generator creates synthetic data samples (pictures of counterfeit drug packaging) that seem like actual data while the Discriminator tries to tell them apart. The suggested pharmaceutical authenticity model uses a GAN.

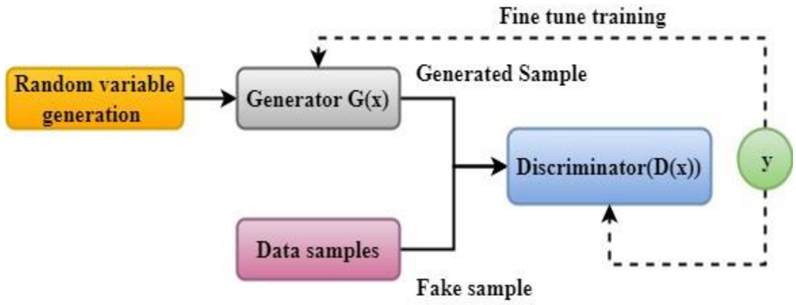

Fig. 2: GAN Model

This model uses a dataset of genuine and counterfeit prescription packaging photos and their associated data. Training the GAN to create synthetic prescription drug patterns that match real-world variances requires this upgraded dataset. The dataset should contain legitimate and counterfeit drug images in various volumes and kinds. Better comprehend feature distribution in genuine Drug Packaging Images by training the GAN with this dataset. Also, create synthetic counterfeit Authentic Drug Packaging Images that seem like real ones. Because of this, the algorithm will detect counterfeit drugs better. The data production process relies on the GAN, famous for its synthetic data synthesis. GANs may train two networks concurrently. The Generator network, the initial network, creates intimate pictures by evaluating data distribution. Discriminator networks detect if input samples are authentic or manufactured, meaning they came from the generator or elsewhere. The GAN-based technique predicts data distribution to discriminate seven target categories while minimizing class variance. GAN loss functions, or min-max optimization functions, are mathematical expressions in Equation 1 representing GAN objectives.

$$min_G max_D v(D,G) = E_{x\sim}pdata(x)[logD(x)] + E_{z\sim}pdata(z)[1 - logD(G(z))] \quad (1)$$

Where $v(D,G)$is the value function defining the objective of GAN, $D(x)$is the discriminators output probability, $G(z)$is the generator output,$E_{x\sim}pdata$denotes the real data distribution and $E_{z\sim}pdata(z)$represents the latent space distribution. Adversarial training helps the Generator-generate more realistic data, and the Discriminator distinguishes between genuine and synthetic samples until both networks attain equilibrium. The Generator creates high-quality counterfeit patterns in this GAN equation, and the Discriminator improves categorization accuracy.

3.3. CNN-based Visual Feature Transaction

After the GAN's training, a CNN classifier independent of the GAN can accept Generator-generated synthetic images. Adding variations to the training dataset improves the classifier and classification quality. CNNs, a deep learning architecture shown in Figure 3, operate well with organized grid data. Such data includes images.

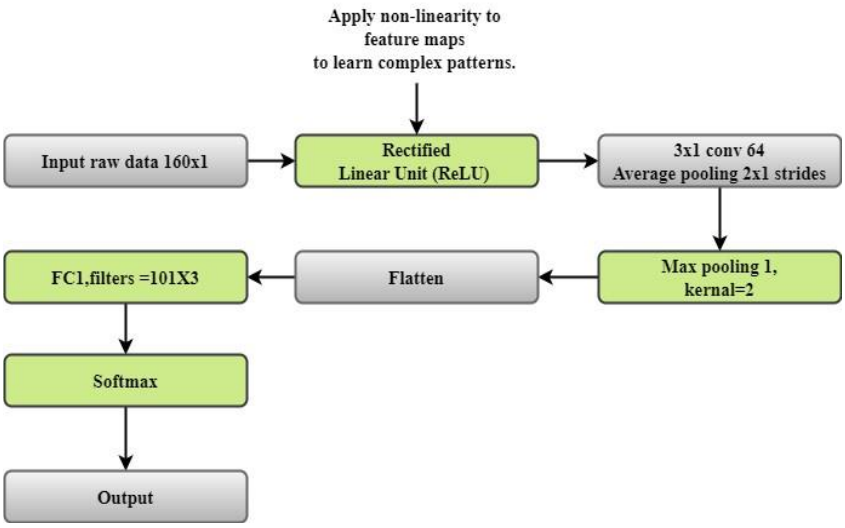

Figure3: CNN Flow Structure based Visual Feature Transaction

Its ability to autonomously acquire hierarchical feature representations from input pictures makes it useful for visual feature extraction. Classifying an input image starts with convolutional, activation, pooling, and fully connected layers. A medicine container image is one example. Deeper CNN layers extract object-specific, sophisticated, and abstract information, while lower-level CNN layers capture textures, patterns, and edges. Such information includes logos, barcode patterns, and packaging design. Visual feature extraction starts with the convolutional layer. It uses a succession of learnable filters or kernels to traverse across the image and multiply and add elements based on their values to produce feature maps. These feature maps collect local visual features and retain spatial relationships between picture components. These features may include holographic elements, printing quality discrepancies, or slight text spacing differences. These attributes may apply to the pharmaceutical industry. This helps the network learn complicated patterns by applying non-linearity to the feature maps created by a Rectified Linear Unit (ReLU) or other non-linear activation function. After that, pooling layers minimize the spatial dimensions of the feature maps, reducing computing effort while preserving the most noticeable qualities. Max pooling, a popular method, selects the highest value from several pixels to protect the most essential properties.

The network uses many convolutional and pooling layers to construct an exhaustive feature depiction of the input image. Each layer catches more subtle patterns like symbol and word placement, fine-grained texturing, and layout modifications. It is crucial to differentiating original from counterfeit packaging. They transfer flattened, deep, high-level features to fully connected (FC) layers. Like standard neural network layers, FC layers use all retrieved features to classify. In multi-class classification, the output layer uses the softmax activation function to create probability ratings for each class (e.g., authentic vs. counterfeit). Due to its ability to learn visual features without manual feature engineering, CNN has performed well in complex tasks like verifying pharmaceutical authenticity, where even minor packaging variations can indicate counterfeit. CNN hierarchies enable good classification accuracy and withstand minor visual distortions, light and perspective changes. Using back propagation, the network optimizes training by changing filter weights to minimize loss between anticipated and actual class labels. It optimizes network performance. Visual feature extraction of the CNN is vital for detecting genuine and counterfeit medications among the many layers of the suggested structure. The next layer of the blockchain uses these classification finds to track records and ensure supply chain integrity. Thus, when used in real scenarios, the system reliably detects and alerts individuals to fake medications.

3.4. Blockchain-Based Record Tracking & Storage

After the CNN finishes visual feature extraction and classification, the suggested method uses blockchain technology to store and track the results safely. The decentralized blockchain ledger stores every classified image and associated metadata, including packing details, timestamps, and unique IDs, and verifies or flags it as counterfeit. This interface provides a safe and transparent audit trail for pharmaceutical verification, ensuring that every classification result is unchangeable and challenging to alter. Blockchain, or distributed ledger technology, makes the system immune to fraud and data manipulation because it allows pharmacies, regulators, producers, and distributors to access and authenticate data independently of a centralized authority. Each certified image has a unique cryptographic hash, which allows the blockchain ledger to maintain data integrity and record all classification findings. After scanning an image, CNNs add a new block to the blockchain with their categorization results and specified properties. Digital signatures and role-based access restrictions can also prevent unauthorized access and changes to sensitive data. In addition to authenticity certification, this comprehensive monitoring and storage method allows real-time data sharing and provenance tracking throughout the pharmaceutical supply chain. Improves traceability and ensures visibility throughout. It's possible to quickly detect and flag counterfeit attempts in the supply chain, protecting producers and customers.The suggested system includes a secure interface for manufacturers, distributors, and regulatory authorities to access, review, and analyze blockchain categorization results. This interface handles user access and authenticity reports. Role-based permissions restrict user access to data fields and functionalities in our system. This protects sensitive data from unauthorized users. The system obtains relevant blockchain records when a user requests an image or pharmaceutical batch. It also creates an authenticity report with CNN-based classification, verification timestamps, and temporal metadata for the objects under investigation. These reports provide authenticity status, supply chain path, and anomaly information, helping stakeholders make smarter decisions. The blockchain also securely records user access, allowing us to track who accessed reports and when. This enhances pharmaceutical verification accountability and transparency.

4. EXPERIMENTAL RESULTS

The proposed model utilizes MedMNIST(https://medmnist.com). A modification of MedMNIST to validate pharmaceutical packaging is possible because it is an extensive, lightweight dataset of medical images intended for various healthcare applications. The massive MedMNIST biomedical picture collection has 12 2D and 6 3D datasets. We pre-processed all photos into 28x28 (2D) or 28x28x28 (3D) formats with classification labels to simplify the process. MedMNIST can handle lightweight 2D and 3D biomedical images with data sizes from 100 to 100,000 and various tasks (binary/multi-class, ordinal regression, and multi-label image representations). These two hundred and eight thousand two-dimensional and ten thousand three-dimensional images have several applications in biological image analysis, computer vision, and machine learning. On analyzing baseline techniques such as two- and three-dimensional neural networks and commercial and open-source AutoML algorithms using MedMNIST. Compared to DT-QMS, ClinAIOps, and AI-BC, the suggested model uses performance parameters such as accuracy, recall and F1-score.

4.1. Accuracy (%)

The proposed model outperforms its rivals by achieving an accuracy rate of 97.8 percent illustrated in Figure 4, demonstrating its efficient ability to distinguish between authentic and counterfeit pharmaceuticals. The DT-QMS achieves an accuracy of 92.3% since it does not concentrate on detecting counterfeits; this indicates that the classification precision is significantly impaired. It accomplishes this by evaluating patient data rather than checking medications which is analogous to how ClinAIOps achieved an accuracy rate of 89.7 percent in its pursuit of optimizing clinical operations. Despite having a success record of 94.1%, the AI-BC supply chain management system, a combination of artificial intelligence and blockchain technology, cannot deal with complex counterfeit patterns.

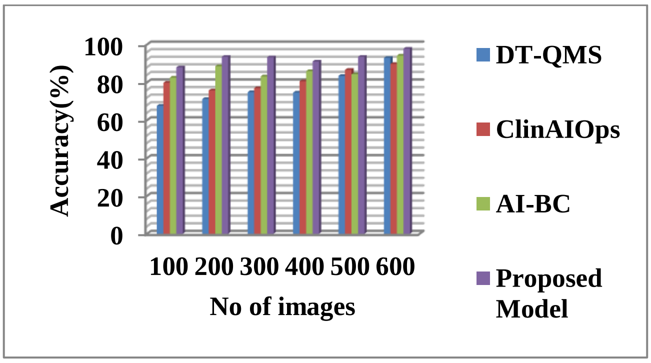

Fig.4: Accuracy

4.2. Recall (%)

The proposed model achieves a recall value of 95.6%, demonstrating that it can identify a significant fraction of genuine counterfeit drugs. Because it takes a more all-encompassing approach to quality assurance measurements, DT-QMS can attain a recall rate of 90.1%, which is slightly lower than the average. The fact that ClinAIOps emphasises optimizing patient data rather than counterfeit identification is mainly responsible for the outstanding success rate of 87.4% that it obtains. The performance of the recommended model is superior to that of AI-BC, which demonstrates that AI-BC is less sensitive when detecting nuanced instances of counterfeiting, although AI-BC has a stronger recall of 91.8%.

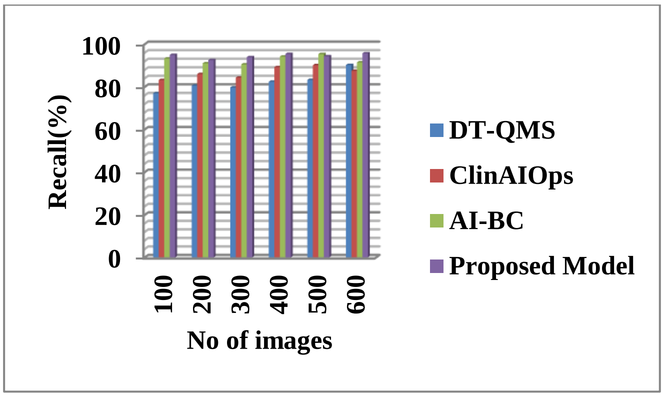

Fig.5: Recall

4.3. F1-score (%)

The proposed model achieves a reasonable balance between recall and precision, as indicated by an F1 score in Figure 6 of 96.7%, which suggests that the model is successful. A good but not particularly impressive level of equilibrium is demonstrated by DT-QMS, which has an F1 score of 91.5%. A lower F1-score of 88.5% is assigned to ClinAIOps due to its improper categorization in pharmaceutical contexts. The F1-score of AI-BC is 93.0%, which indicates that it is not as resilient as the indicated system when confronted with various counterfeit scenarios. This is even though AI-BC performs well overall.

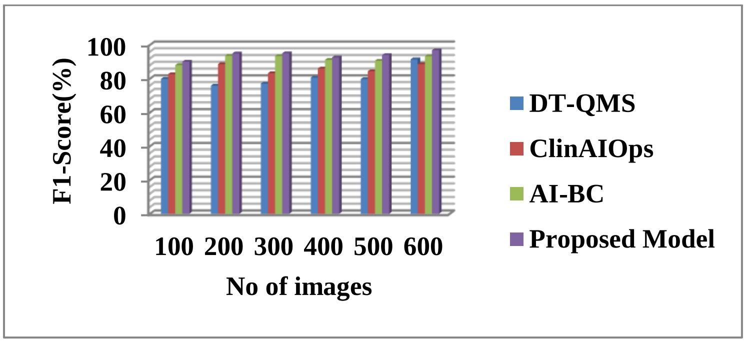

Fig.6: F1-score

5. CONCLUSION

Combining cutting-edge AI techniques like GANs and CNN with multi-layered blockchain architecture improves pharmaceutical validity verification and combats counterfeiting. GANs produce synthetic counterfeit data, and CNNs extract visual features, giving the model better accuracy, recall, and F1-score than DT-QMS, ClinAIOps, and AI-BC. This makes our system highly resistant to manipulation throughout every step. The computational difficulty of GAN training and the possibility of scalability issues in large blockchain networks limit the model's use of high-quality labelled datasets. To solve these problems, future research should focus on lightweight blockchain solutions, optimizing GAN topologies, and federated learning for distributed training that protects users' privacy. Future research may involve creating a library of pharmaceutical photographs, conducting real-world case studies, and using explainable artificial intelligence to improve system dependability and adaptability in changing environments. After these changes, the system will be more reliable and adaptable, allowing it to better handle counterfeit goods' ever-changing threats.

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