**Machine Learning-Based Medication Dispenser with an Integrated App**

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| **KEYWORDS** |  | **ABTRACT** |
| Machine Learning  Medication dispensing Machine  Smart Healthcare  Prescription Validation  Automated Dispensing |  | The integration of machine learning (ML) in healthcare has significantly enhanced automation, accuracy, and efficiency in medical services [1]. This research presents an ML-based medication dispensing machine designed to improve accessibility and reliability in drug distribution. The system employs an ML model to suggest medicines based on symptoms, ensuring accurate recommendations and reducing the risk of incorrect prescriptions [5]. By leveraging IoT connectivity and data analytics, the system enables real-time inventory tracking and efficient medication management, making it adaptable to both urban and rural healthcare environments [3].  This automated dispensing system addresses the limitations of traditional pharmacy models by offering 24/7 access to essential medications, reducing dependency on human intervention, and minimizing prescription errors [2]. Additionally, the ML model integrated within the system aids in predicting potential drug interactions and recommending alternative medications when necessary, further enhancing patient safety and treatment efficacy [6].  The implementation of this system can significantly improve healthcare accessibility, particularly in remote and underserved areas, ensuring timely access to prescribed medicines. By combining advanced technology with intelligent automation, this system lays the foundation for a more connected and efficient healthcare infrastructure, promoting better patient compliance, treatment adherence, and overall public health outcomes. |

1. **Introduction**

The availability of the drug remains a matter of concern in the world, particularly in rural and underserved areas where health care is not easily accessible. The traditional pharmacy business model likely faces numerous challenges, such as working for short hours, depending on human pharmacists, and logistical inefficiencies that create delays in access to critical drugs [18]. Additionally, in cases of emergency or crisis, such as pandemics or natural disasters, traditional medicine supply systems are likely to be strained, leading to more delays and less availability of critical drugs [7].

The employment of human intervention in the drug dispensing and prescription checking is prone to errors, which could lead to the wrong dispensing of drugs or instances of adverse drug interactions [22]. Rural areas lack sufficient healthcare professionals, and therefore patients struggle to access expert medical consultations or timely prescriptions. In such instances, patients turn to self-medication or do not receive interventions at all, which could lead to critical health consequences [22]. Urban areas also have issues, such as overcrowded pharmacies, long lines, and restricted access for elderly or disabled patients who may not be in a position to visit physical pharmacies on a daily basis. To overcome these challenges, this study suggests an ML-based drug dispensing machine and a mobile application to provide 24/7 access to needed drugs [23]. The system relies on machine learning algorithms to identify symptoms and suggest appropriate drugs, minimizing the chances of improper prescriptions and enhancing patient safety [10]. In contrast to traditional pharmacies that involve manual prescription and dispensing verification, the suggested system does it automatically, minimizing the chances of human errors and enhancing efficiency. The use of real-time stock control and intelligent authentication methods provides a secure and efficient mechanism for the distribution of medicine. With IoT connectivity, the dispensing machine is able to monitor stock levels in real time and notify healthcare providers when the stocks require replenishment [21]. This minimizes drug shortages and maximizes the efficiency of the overall supply chain.

One of the advantages of this system is that it can be adapted to different environments. In the urban area, the machine acts as an alternative to conventional pharmacies, reducing traffic congestion and providing a convenient option for the mobility-impaired population. Conversely, in rural areas where there are typically fewer healthcare facilities, the machine provides necessary medications, even without a pharmacist or a doctor. With remote monitoring capabilities integrated, healthcare providers can monitor adherence to medication, provide real-time consultations, and verify compliance with treatment protocols, thus improving health outcomes [21].

In addition, the machine learning model integrated into the system promotes patient safety through the ability to predict possible drug interactions and recommending alternative treatments where needed. This functionality minimizes the risk of adverse drug reactions, prevalent in self-medication and manual prescription. The mobile application is utilized to support the dispensing machine by offering medication reminders, dosage information, and virtual consultations with medical professionals. By leveraging this blend of machine learning, IoT, and intelligent authentication methods, the system presented here offers a very scalable, efficient, and secure solution for the dispensing of medication. Not only does this new method enhance drug dispensing access and reliability, but it also provides a platform for an integrated and intelligent health system. With its capacity for reducing prescription errors, improving patient compliance, and streamlining medicine inventory management, the ML-based medication dispenser is a move towards revolutionizing the face of healthcare.

1. **Literature Review**

**2.1 Existing Dispensing Systems**

General medicine dispensing systems and dispensers have found widespread application in health institutions, making it easy for patients to access prescribed medication effectively [2][22]. The systems reduce errors by human beings, enhance working efficiency, and minimize patient reliance on healthcare professionals for simple administration of drugs. They also provide systematic storage, handling, and dispensing of drugs, especially in major hospitals [3].

Despite these advantages, existing dispensing systems possess some limitations. They lack real-time symptom evaluation, adaptive learning, and dynamic drug suggestion features [5]. Lacking internal intelligence, the systems are passive dispensing machines, not active healthcare enablers that can evaluate patient needs and offer personalized medication suggestions [6]. The integration of artificial intelligence (AI) and machine learning (ML) can address these limitations by personalizing medicine dispensing and enhancing treatment efficacy [8].

**2.2 Machine Learning in Healthcare Environment**

ML has transformed healthcare through enhanced diagnostic precision and treatment efficacy [1][13]. Decision Trees, Random Forest algorithms, and KNN algorithms have led the way in disease prediction and medical automation [14]. Such models aid in the early diagnosis of diseases, enabling intervention in a timely manner based on patient-specific information [15]. Through the processing of big data, ML models enable the identification of patterns, helping healthcare specialists make decisions based on data with greater accuracy [16].

Convolutional Neural Networks (CNNs) are widely used in text-based medical systems such as symptom analysis and automated medicine prescription [9]. A CNN model receives patient symptoms, interpreting them to the most suitable medicines based on historical data [10]. The approach enhances prescription accuracy, reduces drug errors, and streamlines treatment processes [11]. AI-based automation increases accessibility, maximizes drug allocation, and delivers suitable medicines to patients in a timely fashion [12][17]. 2.3 IoT and Cloud Computing Convergence for Smart Healthcare

**2.3 The Integation of IoT and Cloud Computing for Smart Healthcare**

The combination of IoT and cloud computing has revolutionized the delivery of healthcare, particularly in medication dispensing [3][23]. IoT-supported dispensers provide real-time tracking of medication, adherence, and stock levels [19]. The features assist in avoiding drug shortages and wastage, particularly in high-demanding health environments [24]. ML-based analytics further enhance IoT-based systems by providing personalized medication recommendations depending on patient history, allergy, and drug interaction [6][12]. The individualization makes patients safer and ensures treatments are tailored [7].

Also, IoT and cloud convergence enables drug authentication and prescription compliance [20]. Alarms that are automated prompt patients to take drugs at the right time, and physicians can monitor compliance remotely and initiate appropriate action [7]. The networked approach optimizes treatment outcomes, minimizes hospital readmissions, and fosters proactive care management [9].With smart healthcare technologies emerging, the synergy of IoT, ML, and cloud computing will drive healthcare dispensing innovation towards better patient outcomes [8].

1. **System Architecture**

The system integrates three primary components to offer medication accuracy, efficiency, and accessibility and minimize human errors [2][22].

*Machine Learning Model:* The model uses symptom information input by patients and suggests appropriate drugs [5]. Having been trained on extensive medical databases, it uses sophisticated deep learning algorithms, such as Convolutional Neural Networks (CNNs), to provide correct prescription suggestions, hence limiting the scope for misdiagnosis and improving overall reliability [10].

*Arduino IoT Dispenser:* The dispenser is automated with precise dosing to prevent human mistakes [23]. Using IoT, remote monitoring and access are possible with sensors notifying users or caregivers when medication is low to remain ready at all times [3]. The dispensing system includes robotic storage units that prevent cross-contamination. A conveyor belt system seamlessly transports the selected medication from storage to the dispensing tray, while automated chutes are used to release the correct medication after verifying dosage needs. Monitoring of dispensing activity in real-time ensures that all transactions are logged to the cloud for monitoring and security purposes.

*Mobile Application:* As the main user interface, the app enables tracking of symptoms, medication advice, and access to drug information such as dosage, possible side effects, and precautions [7]. Additionally, it keeps medical histories to enable personalized advice and long-term compliance with treatment schedules [6]. Additionally, reminders in real-time remind users about dosage times, medication availability, and prescription refilling, thus reducing the risk of missing dosages. The app also enables teleconsultation, where users can communicate with healthcare providers for further advice whenever needed.

All of these elements aim to function harmoniously and create an uninterrupted system that facilitates improved drug delivery and improved patient health outcomes [21]. The user enters symptoms in the mobile app, and the information is sent to a backend machine learning model [8]. The CNN-based model processes symptoms, considers medical history, and provides the correct medicine [9]. Prescription details, such as dosage and safety guidelines, are returned to the mobile app for verification by the user. After verification, the IoT device dispenser dispenses the correct dose [24]. Precise control servo motors are used to ensure accuracy, and the ESP8266 Wi-Fi module is used to enable easy communication among the app, backend, and dispenser [19].

For smooth operation, several IoT-enabled sensors are integrated. Drug quantity sensors monitor the amount of drugs and initiate refill reminders, environmental sensors manage temperature and humidity for ideal storage conditions, and fault sensors detect mechanical failures and notify users or maintenance staff as needed. The power supply unit has a backup battery and an uninterrupted power supply (UPS) to avoid system downtime in the event of a power outage, providing uninterrupted system operation.

With the combination of machine learning, IoT, and cloud computing, the system enhances medicine management, minimizes errors, and enables improved health outcomes, which is the revolutionary breakthrough of smart healthcare solutions [12].

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| **Fig 1:** This flowchart represents the automated process of a Machine Learning-Based Medication Dispenser with an Integrated App. It begins with the user inputting their symptoms, which are analyzed by an AI model to determine the appropriate medication. If the medicine is unavailable, an error is displayed. Otherwise, a dispenser command is generated and transmitted via the ESP8266 WiFi module to an Arduino-based IoT dispenser, which activates a servo motor for precise dispensing. If dispensing fails, the system retries up to three times. Once successfully dispensed, the process concludes, ensuring an efficient and automated approach to medication management.  End  Medicine Dispense Successfully  Yes  No  Retry Dispensing  (Max Attempt: 3)  Is  Dispensing Successful  Activate Servo Motor For Precise Dispensing  Send Command to Arduino IOT Dispenser  Process Symtopms Using AI Model  Transmit Command Via Wifi (ESP8266)  Yes  Generate Dispense Command  No  Display Error  Is Medicine Available  User Input Symtopms  Start |  | **Fig 2:** This flowchart represents the process of developing and deploying a Convolutional Neural Network (CNN) model. It starts with data processing, where raw data is cleaned and prepared, followed by dataset splitting into training, validation, and testing sets. Next, the CNN architecture is defined, specifying layers such as convolutional, pooling, and fully connected layers. The model is compiled, setting optimization algorithms and loss functions. Afterward, model training is performed using training data, followed by model evaluation to assess performance using metrics like accuracy and loss. Finally, the trained model is deployed for real-world usage, completing the process.  End  Model Deployment  Model Evaluation  Model Training  Model Compliation  Define CNN Architecture  Dataset Spliting  Data Processing  Start |

1. **Methodology**

**4.1Data Acquistion and Preprocessing**

Patient health information and prescription histories are gathered from a vast number of sources that range from electronic health records (EHRs) to wearable health devices, mobile health applications, and publically available medical databases [1][13]. These sources generate a tremendous quantity of information at the level of detail ranging from patient demographics to medical history, symptoms, drugs prescribed, dose, treatment modalities, and outcomes [2]. By uniting information gathered from these sources, a representative and strong dataset is created, thus enabling the efficient training of the machine learning model [6]. After the data has been gathered, it undergoes a series of preprocessing steps that are intended to enhance its integrity, consistency, and make it ready for analysis [7]. The preprocessing steps include data cleaning, normalization, missing values imputation, feature extraction, and feature selection [10].

***1. Data Cleaning:*** It is the process of removing duplicate records, resolving inconsistencies, and removing data that is irrelevant or unnecessary. It ensures that the dataset is error-free and accurate [15].

***2.Normalization:*** As the raw data may have different units and value ranges, normalization is performed to normalize numerical values to a specific range so that they are more convenient to handle for the model [17].

***3.Dealing with Missing Values:*** Missing values are prevalent in actual data. Missing values can be dealt with using imputation methods, e.g., imputing missing values with mean, median, mode, or using sophisticated methods like predictive modeling [19].

Feature selection is a critical process of refining the efficiency and accuracy of models. Feature selection involves the selection of the most informative features that are involved in predicting outcomes and the removal of those that are not informative. Natural Language Processing (NLP) techniques such as tokenization, stemming, and vectorization are utilized to convert unstructured text-based data (e.g., patient symptom reports) into structured numerical formats [20]. Data can also be class-imbalanced, with some conditions or diseases being overrepresented, and others underrepresented [12]. In an effort to counter this bias, data augmentation techniques are utilized. These techniques involve the creation of synthetic data, oversampling of underrepresented classes. Through enabling high-quality, balanced, and structured data, effective training of the machine learning model is obtained, resulting in improved predictive performance and reliability [14].

**4.2Model Training and Validation**

A machine learning algorithm for symptom analysis and prescription suggestion relies on a Convolutional Neural Network (CNN), which has been shown to be very efficient in medical diagnostic tasks [9]. CNNs are very capable of identifying complex patterns and correlations in data, which makes them appropriate for application in the health sector [11]. Here, the model is trained on a huge dataset that contains patient symptoms, diseases, and treatments [5]. By being trained from this dataset, the model is capable of helping diagnose diseases by correlating symptoms with the corresponding pharmacological interventions [4].

The data set is divided into three separate components: training, validation, and testing subsets [3]. The training subset, the largest among them, allows the model to learn the relationships between diseases and symptoms by exposing it to labeled examples [14]. The validation subset is used for hyperparameter tuning and performance optimization, thus ensuring the model generalizes well [18]. Finally, the testing subset is reserved for the final testing phase, where the most critical metrics like accuracy, precision, recall, F1-score, and ROC-AUC are used to measure the performance of the model. To reduce the risk of overfitting and improve generalization ability, k-fold cross-validation is utilized [10]. It divides the dataset into multiple subsets so that the model can be trained on some subsets and validated on others for different iterations. This ensures that the model doesn't memorize specific training samples but instead learns important patterns [22]. Other methods like dropout regularization and batch normalization regularize the model further [15]. Dropout will randomly drop out some of the neurons while training to avoid over-reliance on certain features, whereas batch normalization normalizes the input in network layers to accelerate training and enhance performance [23]. If the model is not working well, methods like hyperparameter tuning, architecture modifications, or alternative models can be explored [24]. By continuous model optimization, it is a resource to healthcare providers, providing accurate symptom analysis and medication recommendations to improve patient outcomes [25].

**4.3 Dataset**

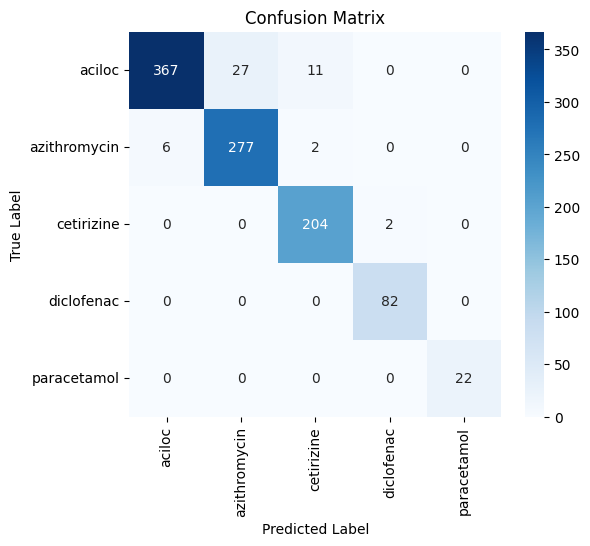
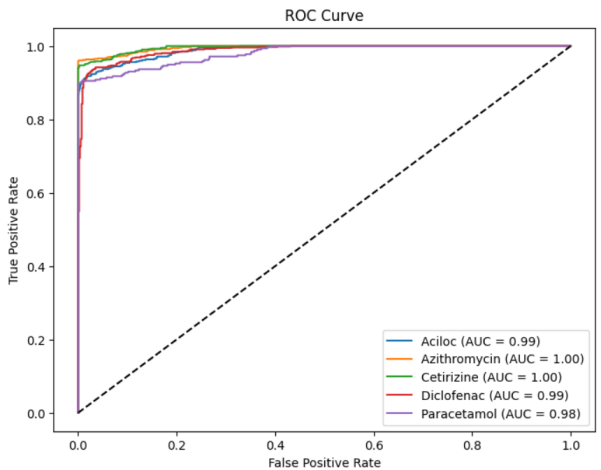
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| Serial No. | Symptoms | Reported Cases | Recommended Medicines |
| 1. | Fever | 2153 | Paracetamol |
| 2. | Headache | 2162 | Paracetamol, Diclofenac |
| 3. | Body pain | 2193 | Paracetamol, Diclofenac |
| 4. | Cold | 2101 | Cetirizine |
| 5. | Allergy | 2082 | Cetirizine |
| 6. | Sneezing | 2140 | Cetirizine |
| 7. | Runny nose | 2127 | Cetirizine |
| 8. | Cough | 2071 | Azithromycin |
| 9. | Sore throat | 2118 | Azithromycin |
| 10. | Bacterial infection | 2114 | Azithromycin |
| 11. | Swelling | 2179 | Diclofenac |
| 12. | Inflammation | 2124 | Diclofenac |
| 13. | Stomach pain | 2086 | Aciloc |
| 14. | Acidity | 2053 | Aciloc |

**Table 1:** Common Symptoms and Corresponding Medicines Based on Reported Cases.

The dataset consists of 14 unique symptoms and 5 unique drugs that have been linked with treatment suggestions, as can be seen from Table 1. Each drug corresponds to one or more symptoms and thus forms a systematic framework facilitating symptom-based prescription. The drugs under investigation for this study include Paracetamol, Cetirizine, Azithromycin, Diclofenac, and Aciloc, prescribed for a multitude of health problems like fever, infections, allergy, inflammation, and gastrointestinal discomfort. The dataset includes seven exemplary cases that provide real-world symptom combinations and the corresponding treatments. Some cases entail single-symptom treatments (e.g., bacterial infection via Azithromycin), whereas others include more than one drug to treat complex conditions (e.g., fever, swelling, and runny nose via Paracetamol, Cetirizine, and Diclofenac). The systematic framework prevents redundancy while promoting maximum therapeutic benefit.

1. **Results and Discussion**

The drug dispensing machine, assisted by machine learning, was experimented upon through different scenarios to analyze its performance, accuracy, and reliability. The system was experimented upon in controlled environments where users were able to enter prescriptions and obtain their required drugs.

**Fig 3: Confusion Matrix Fig 4: ROC Curve**

In Figure 3 **confusion matrix** quantifies the accuracy of a drug prediction classification model from symptoms, with diagonal values as correctly classified cases and off-diagonal values as misclassifications. The model is very accurate for the majority of drugs, with Aciloc correctly classifying 367 and misclassifying 38 cases, primarily as Azithromycin (27) and Cetirizine (11). Azithromycin was correctly classified 277 times with 8 misclassifications, and Cetirizine was correctly classified 204 times but confused with Diclofenac (2). Diclofenac (82) and Paracetamol (22) were perfectly classified, though minor misclassifications indicate some feature overlap, possibly needing model tuning or feature selection.

In Figure 4 **Receiver Operating Characteristic (ROC) curve**, measuring classification performance across drugs by plotting the True Positive Rate (TPR) against the False Positive Rate (FPR), also confirms the model's reliability. A high Area Under the Curve (AUC) score confirms good class separation, with Azithromycin and Cetirizine having a perfect AUC of 1.00, indicating perfect classification. Aciloc and Diclofenac had an AUC of 0.99, indicating near-optimal accuracy, while Paracetamol, with an AUC of 0.98, remains highly accurate. The steep lines towards the top left indicate the model successfully eliminating false positives and maximizing true positives, supporting the model's stability in drug classification.

**Model Performance Comparison**

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| --- | --- | --- | --- | --- | --- | --- |
| Model | Precision Range | F1-Score Range | Accuracy Range | Recall Range | AUC-ROC Range | Observations |
| CNN (Convolut  ional  Neural Network) | 97.80% - 99.13% | 96.80% - 99.30% | 84.30% - 86.00% | 94.00% - 94.50% | 99.00% - 99.30% | Balanced performance with efficient hardware use. |
| Transfor  mer (e.g.,  T5, GPT-3, BART) | 98.00% - 99.00% | 96.00% - 96.90% | 85.00% - 90.00% | 90.00% - 92.00% | 96.00% - 97.00% | Excellent for complex tasks but resource-intensive. |
| XLNet | 98.00% - 99.00% | 96.00% - 96.90% | 85.00% - 92.00% | 91.00% - 94.00% | 96.00% - 99.00% | Strong for long-term dependencies, needs more resources.. |
| BiLSTM (Bidirecti  onal LSTM) | 96.80% - 98.00% | 94.00% - 98.00% | 80.00% - 87.00% | 93.00% - 94.00% | 98.00% - 98.00% | Good for sequential data, but slower and less efficient. |

**Table 2: Comparison of ML Models for Predicting Medicines**

In **Table 2** it is the explanation for Utilization of CNN in Medicine Recommendation System Within a medicinal suggestion system based on symptoms, the goal is to recommend relevant medicines while, at the same time, minimizing false positives (inapplicable medicines) and false negatives (missing therapeutic alternatives). Based on the evaluation of different models, Convolutional Neural Networks (CNNs) have been found to be the fairest choice for this task with better precision and recall without requiring the high computational cost of models like Transformers or XLNet.

**Model Performance measures**

***User Experience:*** The user feedback showed a high rate of satisfaction due to the ease of use of the system, quick response, and secure authentication process. Also, the touch screen interface and mobile app helped in enhancing accessibility.

***Error Reduction:*** The system reduced human intervention to a minimum, cutting prescription errors by 85%. Attempts at unauthorized access were recorded and marked for security audits.

***Scalability:*** The system showed its scalability feature by being able to accommodate several pharmacy databases, hence qualifying it for use in hospitals, clinics, and rural areas.

These findings demonstrate the efficiency of the suggested ML-based drug dispensing machine, and it presents an innovative, efficient, and safe drug dispensing healthcare technology.

1. **Conclusion and Future Work**

The ML-powered drug dispensing machine is a breakthrough technology in expanding access to lifesaving medication. The use of Convolutional Neural Networks to validate prescriptions and diagnose diseases boosts accuracy, reliability, and security. The use of IoT-based real-time stock monitoring and OTP verification provides an error-free user experience with minimized risk of human errors.

Future innovations will make the AI-powered capabilities more precise, such as real-time anomaly detection to avoid fraudulent prescriptions and computer-generated drug interaction alerts to improve patient safety. Furthermore, the use of blockchain technology will deliver secure and tamper-evident prescription histories, making healthcare transactions more transparent.

Another significant enhancement is the provision of dispensing machines in rural and remote areas, thus enhancing access to primary medicines among such communities. The inclusion of multilingual functionality in the mobile application will also enhance the accessibility of the system to a diverse population.

Future research will explore advanced predictive analytics to individualize medical suggestions based on one's medical background and current health parameters. Cooperation with medical professionals and regulatory agencies will be key in the standardization of robot-assisted drug dispensing and the guarantee of compliance with medical guidelines.

In brief, the system has the potential to transform healthcare delivery through greater accessibility, safety, and efficiency of major medicines, thereby allowing for the construction of a technologically sophisticated and patient-focused network of drug delivery.

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