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NEURAL NETWORK MODEL FOR OPTIMIZED MANAGEMENT OF MEDICINES IN A UNIVERSAL FIRST AID KIT

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Abstract. *A modified convolutional neural network model MediPackNet was developed with an accuracy of 92%, which correctly recognized all 5 test images of medicines. It showed good results at the level of 6 models based on already known ones, namely: InceptionV3, Xception, ResNet50V2, MobileNetV2, NASNetMobile and DenseNet169. In addition, AES, RSA data encryption methods and a combination of these algorithms were implemented. Based on the results of the analysis, it was concluded that hybrid encryption is the best for the developed software. A mobile application for the accounting of medicines for a universal first aid kit was created, with stable performance and the possibility for further development. The developed application has the potential to significantly facilitate the process of managing medicines stocks and contributes to more efficient use of medical resources and procurement optimization. In addition, the ability to track the course of treatment contributes to a more accurate following of medical recommendations and ensures more effective health monitoring. The use of the mobile application also has a significant impact on the environment, as it reduces the amount of hazardous waste associated with improper storage and disposal of expired medicines.*

Keywords: *accounting, medicines, first aid kit, packaging, recognition, mobile application, .NET MAUI, Python.*

Introduction

Medicines play an extremely important role in a person's life, helping to maintain health and improve quality of life. However, people often skip taking their medications or overpay for medications they already have at home, but don't remember about them. The World Health Organization has classified medication non-adherence as a major global problem [1]. It is estimated that 20% to 50% of patients do not take their medications properly [1]. The reasons for this are quite diverse, but the most common reasons are unintentional, such as confusion or simple forgetfulness. These problems can have serious health consequences and increase treatment costs [2]. In this regard, there is a need for a convenient and efficient medication management tool. The universal first aid kit medicine accounting software is a relevant solution to solve these problems. It allows you to add, delete, and edit first aid kits' medicines, monitor their expiration dates, and also makes it possible to set up reminders to take medicines. This is especially useful for people who take a lot of medications or have chronic diseases [3].

Using a mobile application for accounting is convenient and affordable, as a mobile phone is usually always with the owner. It also has a significant impact on the environment, as it reduces the amount of hazardous waste associated with improper storage and disposal of expired medicines.

1 Analysis of known methods and available software tools

In order for a first aid kit to be effective and safe, it is necessary to keep proper records of the medicines it contains. This is extremely important, since human life and health depend on the correct use and proper condition of these medicines. The subject area of medicines accounting in the first aid kit is the pharmaceutical industry. To develop it, it is necessary to have knowledge of various medicines, their effects, classification, dosage forms, expiration dates, dosages, and routes of administration.

1.1 Review of existing methods

The task of accounting for medicines in a first aid kit is not new, as people have long been using first aid kits to store medicines. The technology development has made its implementation more convenient, efficient, and accessible to users.

There are several methods of performing the task of accounting for medicines in the first aid kit, namely: manual accounting, scanning barcodes, recognizing images of medicines packages. Manual accounting involves entering data about medicines manually. The user can enter the name, expiration date, quantity, and other information about each medicine as needed. This method is simple but can be time-consuming and labor-intensive.

Mobile applications can use a smartphone camera to scan barcodes located on drug packages [4]. After scanning, the application automatically finds the medicine in the database and adds it to the list of medicines. This method is convenient and fast, as it avoids manual data entry. However, it depends on the availability of barcodes on packages and the database with medicines and their code values.

The software can use an image recognition system to identify medicines [5]. The user can take a photo of the medicine's packaging, and the application will automatically add this medicine to the list of medicines. This method makes it easy to add new medicines to the list, but the accuracy of the recognition may depend on the quality of the image, the model, and the recognition database.

Manual accounting and package image recognition methods were chosen for further implementation because they make the accounting process more accessible and convenient for a wide range of users. A person will be able to choose a method of accounting that meets their needs, namely, entering data manually, recognizing the medicinal product by its packaging, or combining these methods.

Image recognition can be a more versatile method than barcode scanning, as it allows you to keep track of a variety of medicines, regardless of the type of barcode or its presence, packaging damage, differences in design or localization.

1.2 Review of image classification approaches and techniques

Traditional classification is a key data analysis approach that focuses on sorting data points into predefined classes or categories using specific rules and established features. Prior to the rise of deep learning, various conventional techniques such as Decision Trees, Support Vector Machines (SVM), Naive Bayes, and k-Nearest Neighbors (k-NN) were commonly applied for this task [6]. These methods were used and described in studies [6, 7, 8, 9, 10, 11, 12].

A Decision Tree (DT) is a hierarchical, rule-based method that utilizes a non-parametric approach [7]. It determines class membership by recursively dividing a dataset into homogeneous subsets. As a hierarchical classifier, it allows the acceptance or rejection of class labels at each intermediate step. The process consists of three main stages: partitioning the nodes, identifying the terminal nodes, and assigning class labels to these terminal nodes.

Kernel SVMs implicitly transform input feature vectors into a higher-dimensional space through the use of a kernel function, such as the Gaussian kernel [8]. In this transformed space, a maximal separating hyperplane is constructed, particularly for a two-class problem. Two parallel hyperplanes are then created symmetrically on either side of the separating hyperplane. The goal is to maximize the distance, known as the margin, between these two outer hyperplanes. It is believed that the larger the margin, the lower the generalization error of the classifier. SVMs are based on the principle of structural risk minimization, which aims to minimize an upper bound on the generalization error, unlike many classifiers that focus on minimizing empirical risk, or the error on the training set. The SVM algorithm works to find a decision function that minimizes a specific functional. Moreover, SVMs are capable of training nonlinear classifiers in high-dimensional spaces even with a small training set, thanks to the selection of a subset of vectors, known as support vectors, which define the optimal boundaries between the classes [8].

The Naive Bayes classifier operates on a probabilistic framework, assigning the class with the highest estimated posterior probability to the feature vector derived from the region of interest (ROI) [9]. This method is optimal when the attributes are independent (orthogonal), but it still performs well even without this assumption. Its simplicity enables strong performance with small training sets, and by constructing probabilistic models, it remains robust to outliers. Additionally, Naive Bayes creates soft decision boundaries, helping to prevent overfitting. However, the arbitrary choice of the distribution model for estimating probabilities P(x) and the limited flexibility of its decision boundaries can reduce its effectiveness in more complex multiclass problems [9].

The k-Nearest Neighbor classifier defines hyperspheres within the instance space by assigning the majority class of the k-nearest instances based on a specific metric. It is asymptotically optimal and allows fast testing [10]. However, this method has several limitations. It is highly sensitive to the curse of dimensionality, as increasing the dimensionality tends to disperse the feature space, causing the local homogeneous regions representing the class prototypes to spread out [11]. The classification performance strongly depends on the chosen metric. Additionally, selecting a small value for k can lead to erratic decision boundaries, making the classifier more susceptible to outliers.

Although these methods are effective in many situations, they often require manual feature engineering, which can be labor-intensive and may not capture the complex patterns and relationships within sophisticated datasets. The chosen features are then used as inputs for the classification algorithms, which follow set criteria to assign data points to the appropriate classes [12].

With the rise of deep learning, Convolutional Neural Networks (CNNs) emerged as a powerful alternative, offering significant advancements in processing and analyzing data with complex structures, such as images and videos. Studies [6, 13, 14] highlight the effectiveness of CNNs in various applications, demonstrating their ability to achieve superior results.

Convolutional Neural Networks are a regularized form of multilayer perceptrons, which are typically fully connected networks where each neuron in one layer is linked to every neuron in the next [13]. CNNs differ by employing a mathematical operation called convolution instead of standard matrix multiplication in at least one of their layers. As a type of feedforward neural network, CNNs are particularly suited for handling data with grid-like structures. They learn features and patterns within the data using convolutional layers. The neurons in a CNN have learnable weights and biases, where each neuron processes inputs, performs a dot product, and may apply a non-linearity [14]. CNNs are inspired by biological processes in the visual cortex of the brain and have become a key solution for many computer vision tasks in artificial intelligence, such as image and video analysis.

Unlike traditional methods, CNNs leverage layered architectures to automatically learn and extract features from raw input data, significantly improving performance in tasks involving visual recognition and pattern detection.

1.3 Review of available software tools

First aid kits are an integral part of our lives. These are small containers that contain a variety of medical supplies and medications needed for minor medical interventions or first aid. They can be present at home, at work, in schools, cars, etc.

It is important to properly maintain the first aid kits and keep good records of the medicines they contain. This is necessary to ensure the safety and effective use of medicines in case of emergency. It is also important to have a clear list of medical supplies and update it in a timely manner to have complete information about available resources when needed.

Currently, there are already software tools [15, 16, 17, 18, 19, 20, 21, 22] that ensure the accounting of medicines. These programs allow you to accurately track the availability and quantity of medicines, control expiration dates, etc.

These software tools typically provide the ability to create lists of medicines, enter information about each product, and indicate the number of units available. Some of them even allow you to scan barcodes on drug packages to automatically fill in the data. In addition, the programs can display alerts about the approaching expiration date or shortage of certain medicines, which allows you to replenish stocks in a timely manner.

But in addition to the main advantages, some of them have disadvantages. For example, there is no tracking of the course of treatment and reminders to take medications if the user needs it, and no import of their own first aid kits.

The implemented mobile application has the following advantages over existing analogues: tracking the course of treatment, medication reminders, and recognition of certain medicines by their packaging.

2 Development of a modified convolutional neural network model MediPackNet

To implement the function of recognizing medicines from images of their packages in the software, a modified convolutional neural network model MediPackNet and 6 more models based on the already known ones were created, namely: InceptionV3, Xception, ResNet50V2, MobileNetV2, NASNetMobile, and DenseNet169 [23, 24, 25, 26, 27, 28, 29, 30]. The training results of these models were used to compare, analyze, and improve the models.

The following medicines were selected for recognition: Flucold-N, Gofen 200, No-Spa, Ortophen-Zdorovye Forte, and Phosphalugel.

The created model contains convolutional layers, maximum pooling layers, flatten layers, dropout layers, and fully connected layers. In addition, the images were normalized and randomly rotated, zoomed, and flipped horizontally to increase the diversity of the data (in all created models) [31, 32, 33]. ELU (Exponential Linear Unit) was chosen as the activation function because it showed the best results among the available functions. The output layer uses the Softmax activation function (5 classes). In the fully connected layers, L2-regularization was used (encourages smaller, more evenly distributed weights by adding a penalty), which improved the resulting model. The structure of this model is shown in Figure 1.

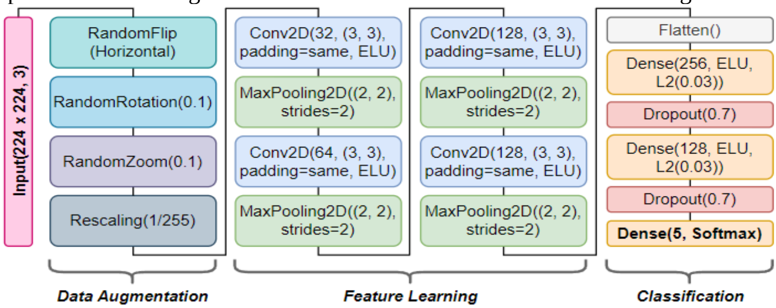

Figure 1. Structure of the MediPackNet model

The other 6 models include Inception V3, Xception, ResNet50V2, MobileNetV2, NASNetMobile, and DenseNet169, a global average pooling layer, and fully connected layers. The structure of these models using the example of the InceptionV3-based model is shown in Figure 2.

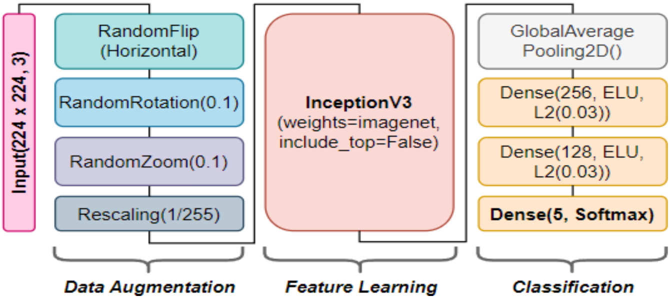

Figure 2. Structure of the model with Inception V3

3 Software implementation

3.1 Software structure

To design the architecture of the mobile application, the Model-View-ViewModel (MVVM) design pattern was used [34].

Software data is stored in a database that has been created and interacted with using SQLite.

The structure of a mobile application consists of 27 classes and 6 XAML (eXtensible Application Markup Language) files with 6 classes associated with them. The classes of view models and views have ViewModel and View in their names, respectively. All program files are structured into folders according to their purpose. The classes in the General folder were designed to support the interaction of views with view models.

The structure of the server part of the program consists of 5 files, 3 of which are responsible for creating a model for medicine recognition, and the rest for processing HTTP requests, encryption, decryption, and image recognition.

The architecture of a mobile application contains three functional parts: model, view, and view model. The diagram of classes representing the modules of the part containing the models is shown in Figure 3.

The diagram of classes representing the modules of the part containing the view models is shown in Figure 4.

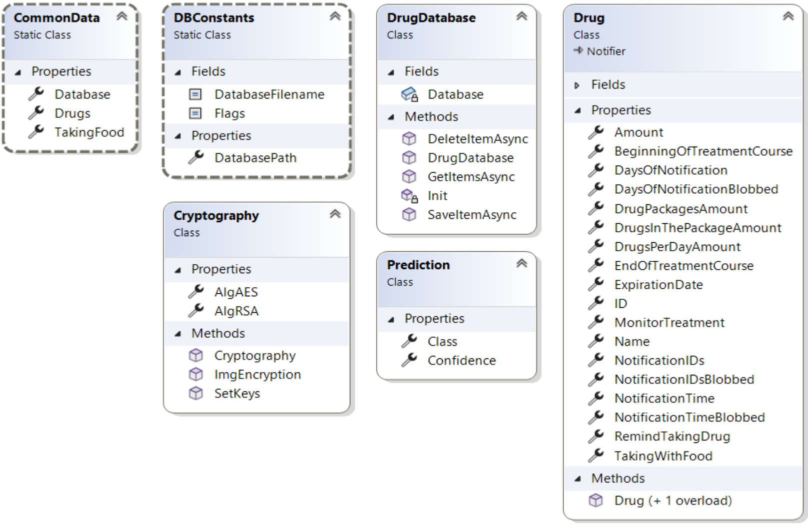

Figure 3. Diagram of classes that belong to models

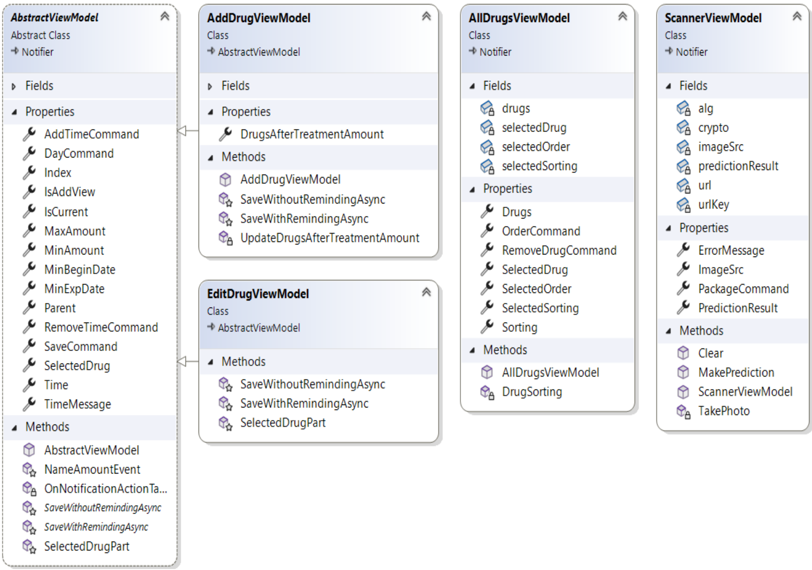

Figure 4. Diagram of classes that belong to view models

The diagram of classes representing the modules of the part containing the views is shown in Figure 5.

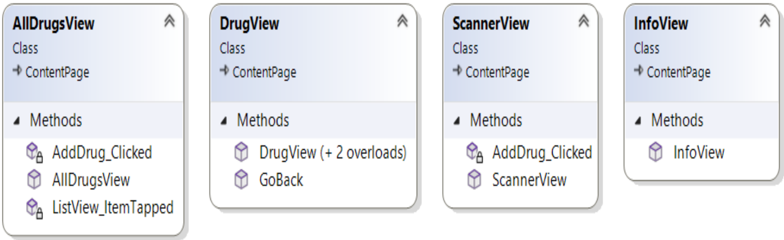

Figure 5. Diagram of classes that belong to views

The server part consists of three modules: cryptography, recognition, and creation of a model for recognition.

3.2 Image encryption

To implement the image encryption function in the software, modules were created that encrypt and decrypt data using the symmetric AES algorithm with CFB mode, the asymmetric RSA algorithm, and a combination of these algorithms [35, 36, 37, 38, 39]. The results of implementing these methods were used to compare, analyze, and select the best approach to protecting visual information [40, 41, 42].

In this application, encryption is essential because the images of medicine packages may include sensitive data such as personal annotations, prescription labels, QR codes, or barcodes that can be associated with specific users. If transmitted in plain form, such images could potentially be intercepted and analyzed, leading to privacy breaches, exposure of medical conditions, or manipulation of user medication data.

Using the System.Security.Cryptography library, the Cryptography class was created to encrypt images of medicine packages using AES and RSA algorithms and decrypt the shared key (encrypted with RSA in the hybrid approach). After encryption, the images are transmitted to the server.

On the server side, the Cryptography module (built with PyCryptodome) decrypts the received images and encrypts shared keys using RSA for secure communication. Keys are transmitted via HTTP requests, making asymmetric and hybrid encryption more suitable due to their resilience to insecure channels.

To assess the efficiency of the implemented encryption strategies, test sessions were conducted using typical medicine package images transmitted over a network. The hybrid approach (AES for image data + RSA for key exchange) showed a balanced trade-off between performance and security, with an execution time of 1.44 seconds, which is acceptable for real-time usage.

The characteristics of the encryption methods are summarized in Table 1.

Table 1

Comparison of implemented encryption methods

Comparison criteria	AES	RSA	AES and RSA
Keys	One shared key	Private and public keys	Key combination
Key size	256 bits	2048 bits	256 and 2048 bits
Time of execution	1.09 s	51.47 s	1.44 s
Complexity of key management	High	Low	Low
Transfer of keys	Difficult	Easy	Easy
Complexity	Low	High	Medium

The table shows that each method has its advantages and disadvantages. AES is known for its speed and efficiency in encrypting large amounts of data, while RSA provides secure key exchange and a high level of security, but may be less efficient for large amounts of data. The hybrid method leverages the strengths of both: using AES for data encryption and RSA for key exchange, ensuring security without compromising performance. Therefore, hybrid encryption is best suited for protecting visual medical data in a client-server application.

3.3 Recognition models training

In addition to ensuring data security, an important component of the project is to recognize medicines by their packaging. For this purpose, the created recognition models were trained and the results are shown in the form of graphs in Figures 6-12.

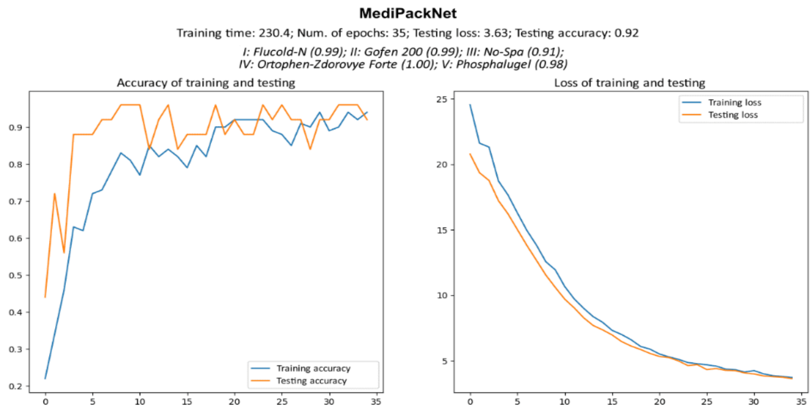

Figure 6. Training result of the MediPackNet model

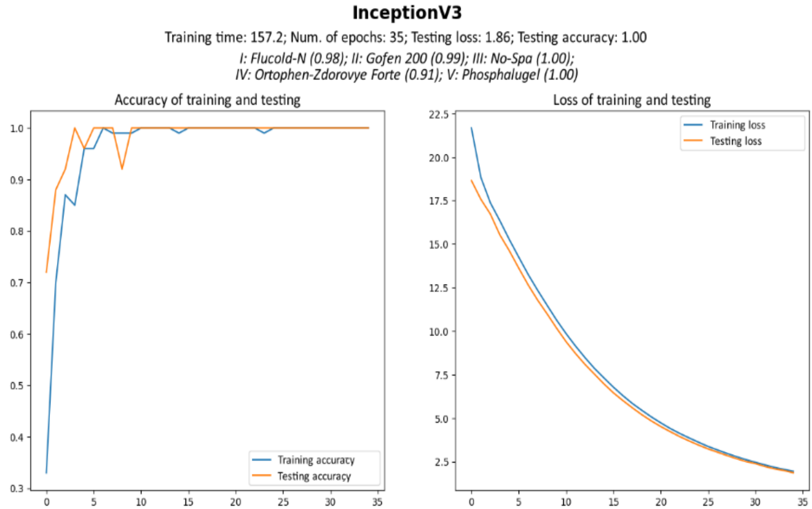

Figure 7. Training result of the model with Inception V3

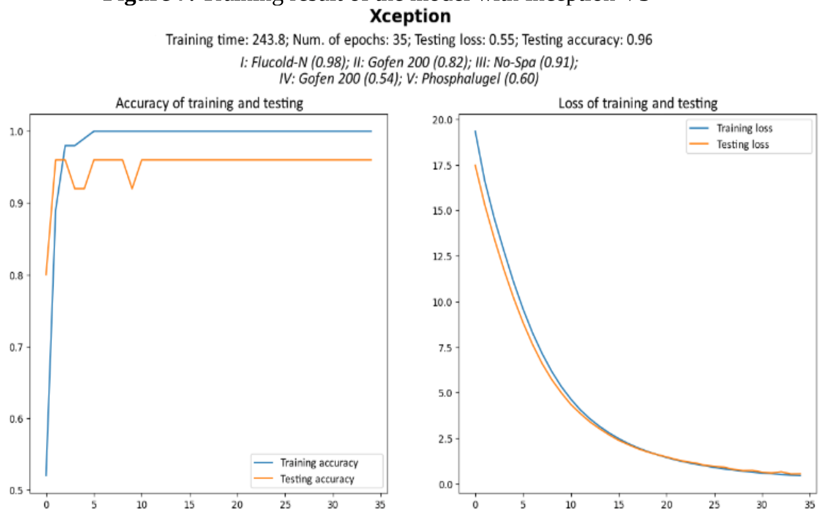

Figure 8. Training result of the model with Xception

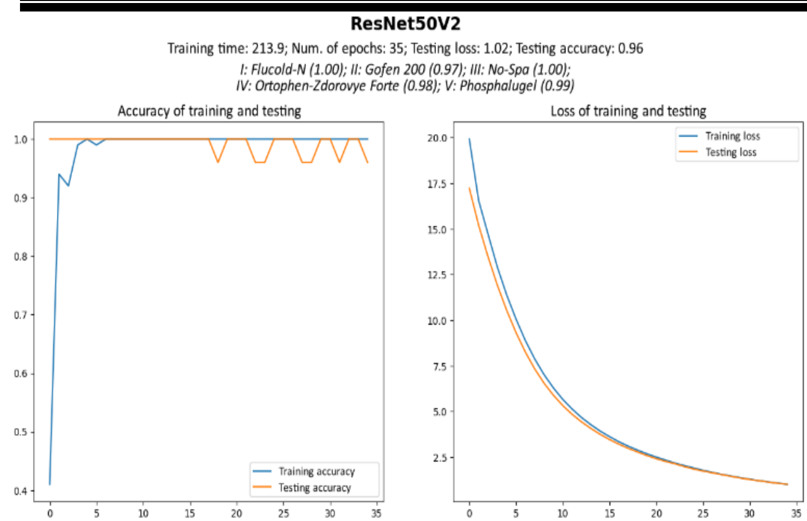

Figure 9. Training result of the model with ResNet50V2

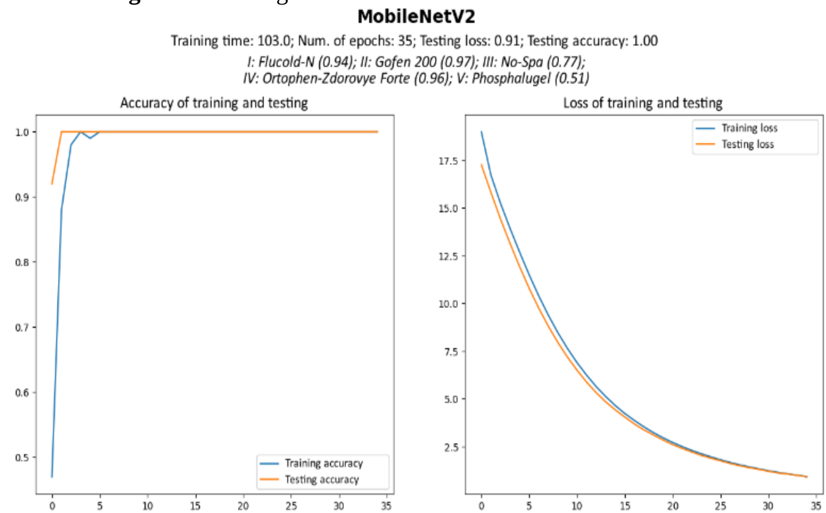

Figure 10. Training result of the model with MobileNetV2

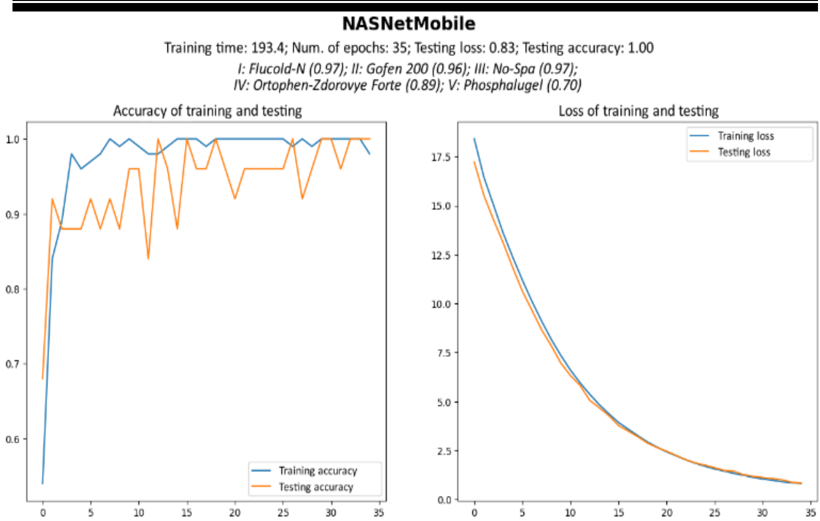

Figure 11. Training result of the model with NasNetMobile

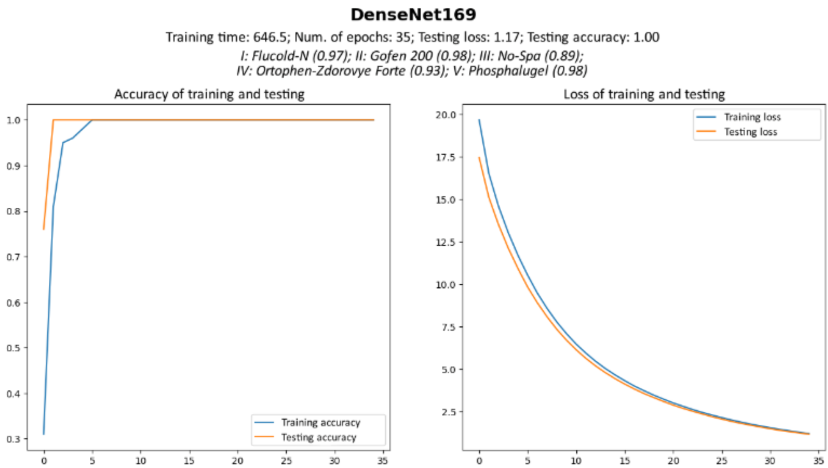

Figure 12. Training result of the model with DenseNet169

3.4 Graphical user interface

During the development of the mobile application, a user-friendly graphical interface was implemented to facilitate intuitive interaction with the core functionality of the system:

"My Medicines" tab: This tab serves as the main screen where users can view and manage their list of medications. Medicines are displayed in a sorted list. The "Add Medicine" button allows the user to quickly navigate to the medicine input page;

"Add Medicine" page: This interface enables users to input detailed information about a new medicine. It also allows users to configure reminders for each medication. Upon completing the form, the user can save the medicine entry using the "Save" button;

"View Medicine" page: Once a medicine is added, it can be viewed and edited in this interface. All previously entered fields are displayed, and users can adjust the treatment parameters or notification settings as needed;

"Recognition" tab: This tab provides a convenient way to identify medications using image recognition. Users can take a photo of the medicine packaging via the "Packaging" button. The recognized name is displayed on-screen, and users can then proceed to the "Add Medicine" page with pre-filled data based on the recognition result;

"Info" tab: This section contains information about the application and developer.

Figure 13 presents examples of the key interface screens.

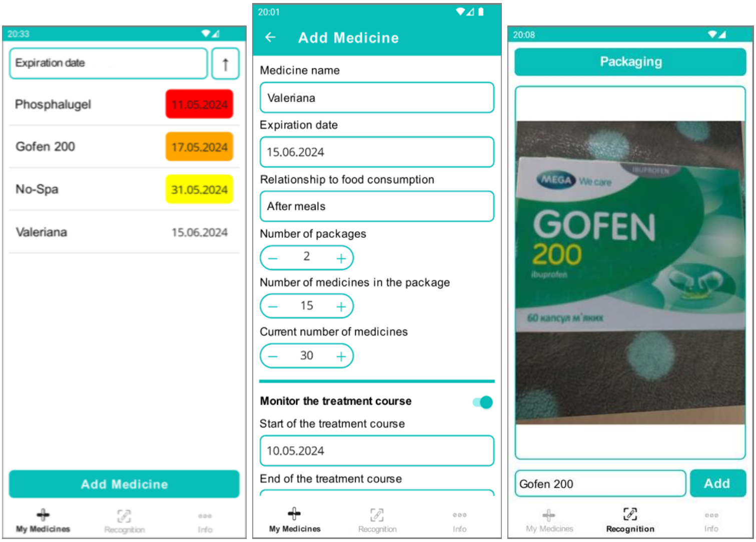

Figure 13. Key interface screens.

Testing the developed software and studying the effectiveness of the developed recognition models

For the training set, 100 images of 5 different medicine packages (20 images per medicine) were used, and for the test set, 25 images (5 per medicine). To ensure data variability and model robustness, the images were captured under diverse real-world conditions: both good and poor lighting, from different angles and distances, and with packaging in different states (e.g., in cardboard boxes and without them, if applicable). The dataset includes variations in background and orientation to simulate common usage scenarios in mobile applications.

Table 2 shows the results of training the model over 35 epochs. To further validate the model's performance, 5 additional images per class that were not included in the training or test set were used. The number of correctly classified samples is shown in Table 2, and their class probabilities are presented in Table 3.

To provide a more comprehensive assessment of model performance, standard classification metrics - accuracy, precision, recall, and F1-score- were calculated for each model on the test set. A comparison of these metrics is provided in Table 4. MediPackNet achieved an accuracy of 92%, with a precision of 93% and an F1-score of 91%. However, confusion matrix analysis revealed that MediPackNet misclassified two samples of the third class (No-Spa), leading to false negatives.

Table 2

Comparison of model training results

Model	Train. time (s)	Test loss	Test acc. (%)	Size (MB)	Number of correctly classified samples
MediPackNet	230.4	3.63	92	78.3	5 з 5
InceptionV3	157.2	1.86	100	97.5	5 з 5
Xception	243.8	0.55	96	90.8	4 з 5
ResNet50V2	213.9	1.02	96	101	5 з 5
MobileNetV2	103.0	0.91	100	18.0	5 з 5
NASNetMobile	193.4	0.83	100	39.9	5 з 5
DenseNet169	646.5	1.17	100	67.7	5 з 5

Table 3

Image classification probabilities in percentage

Model	Flucold-N	Gofen 200	No-Spa	Ortophen-Zdorovye Forte	Phosphalugel
MediPackNet	99	99	91	100	98
InceptionV3	98	99	100	91	100
Xception	98	82	91	–	60
ResNet50V2	100	97	100	98	99
MobileNetV2	94	97	77	96	51
NASNetMobile	97	96	97	89	70
DenseNet169	97	98	89	93	98

Table 4

Comparative evaluation of models using key classification metrics (%)

Model	Accuracy	Precision	Recall	F1-score
MediPackNet	92	93	92	91
InceptionV3	100	100	100	100
Xception	96	97	96	96
ResNet50V2	96	97	96	96
MobileNetV2	100	100	100	100
NASNetMobile	100	100	100	100
DenseNet169	100	100	100	100

The data demonstrates that the custom MediPackNet model was able to learn effective feature representations from a relatively small but diverse dataset. Although some pre-trained models achieved perfect accuracy, MediPackNet provided reliable performance with minimal misclassifications and offers advantages in flexibility and deployment. Its robust behavior in real-world-like conditions and interpretability made it suitable for integration into the server-side application, with further improvements expected as the dataset and architecture evolve.

The software was tested on an emulator of a mobile device with Android OS with the following characteristics: model: Google Pixel 5; OS version: Android 14.0 (API 34); screen size: 6.0 inches; screen resolution: 1080x2340 pixels, 440 dpi; processor: x86_64; memory: 1 GB; network access; access to front and back cameras; sensor support [41, 42, 43, 44].

During the testing of the mobile application, various scenarios were executed, including checking the functionality, stability, interaction with the server side, correct data storage and processing.

4 Discussion of the research results

The software was created for which a modified convolutional neural network model MediPackNet was developed, which is 92% accurate and correctly recognized all 5 test images of medicine packages. It showed good results at the level of 6 models based on already known ones, namely: InceptionV3, Xception, ResNet50V2, MobileNetV2, NASNetMobile and DenseNet169. In addition, AES, RSA data encryption methods and a combination of these algorithms were implemented. Based on the results of the analysis, it was concluded that hybrid encryption is the best for the developed software. All the planned functions were implemented in the software. Testing of the program proved that all the developed functionality works correctly.

The results of the comparative analysis show that the proposed MediPackNet model demonstrates high accuracy and efficiency. It is important to note that the model architecture was optimized to achieve this level of accuracy. Successful recognition of all test images confirms the reliability and stability of the developed software. The implementation of data encryption methods ensures a high level of security of information transmission, which is critical for the medical field. Further research can be aimed at optimizing computational complexity and reducing data processing time, as well as expanding the functionality of the software. The results of the study are of great practical importance and can be used in various industries that require the ability to keep records of medicines and high accuracy of package image recognition.

The disadvantage of using package recognition is the need to constantly update the training set and additional training of the created model due to periodic changes in medicines packaging.

The developed application has the potential to significantly facilitate the process of managing medicines stocks and contributes to more efficient use of medical resources and optimization of procurement. In addition, the ability to track the course of treatment contributes to more accurate implementation of medical recommendations and ensures more effective health monitoring. The use of the mobile application also has a significant impact on the environment, as it reduces the amount of hazardous waste associated with improper storage and disposal of expired medicines.

In the future, it is possible to improve the created software by adding notifications about the need to purchase a medicine because it is about to expire, implementing barcode or serial number scanning, improving the package recognition model, security mechanisms, and expanding the list of medicines for recognition, providing the ability to view instructions for use of medicines, etc.

Conclusions

The subject area was analyzed, the relevance and feasibility of software development were presented, the known methods of performing the task of accounting for medicines of a universal first aid kit were considered. In the course of analyzing the analogues, their advantages and disadvantages were identified and the functionality for implementation was determined.

The chosen design pattern and the architecture of the developed software were described. The MediPackNet model for recognizing medicines by their packaging was developed, which contains convolutional layers, maximum pooling layers, flatten layers, dropout layers, and fully connected layers. The images were normalized and randomly rotated, zoomed, and horizontally flipped to increase the diversity of the data (in all created models). ELU was selected as the activation function, and the output layer uses the Softmax activation function. L2 regularization was used in the fully connected layers. There were 6 more models created, which include Inception V3, Xception, ResNet50V2, MobileNetV2, NASNetMobile, and DenseNet169, a global average aggregation layer, and fully connected layers. Based on the results of training and testing, it was decided to use the MediPackNet model, which is 92% accurate and correctly recognized all 5 test images of medicine packages. A conceptual model of the database with the "Medicine" entity was developed. Then the implemented data encryption methods

AES, RSA and a combination of these algorithms were described. Based on the results of the analysis, it was concluded that hybrid encryption is the best for the developed software. The main decisions regarding the development of the graphical user interface were also presented.

References

1. Pérez-Jover, V., Sala-González, M., Guilabert, M., & Mira, J. J. (2019). Mobile Apps for Increasing Treatment Adherence: Systematic review. Journal of Medical Internet Research, 21(6), e12505. https://doi.org/10.2196/12505.

2. Nova Advertising. (2023). Why medication dosage monitoring is critical for your health. Texas Star Pharmacy. https://www.texasstarpharmacy.com/why-medication-dosage-monitoring-is-critical-for-your-health/.

3. Hladka, O. (2022). Complete overview of medication tracking software — Intellectsoft blog. Intellectsoft Blog. https://www.intellectsoft.net/blog/medication-tracking-software/.

4. Abdulhamid, M., & Matongo, A. (2020). Mobile phone and barcode scanner. Scientific Bulletin of Electrical Engineering Faculty, 20(1), 25–28. https://doi.org/10.2478/sbeef-2020-0105.

5. Avola, D., Cinque, L., Fagioli, A., Foresti, G. L., Marini, M. R., Mecca, A., & Pannone, D. (2022). Medicinal boxes recognition on a deep transfer learning augmented reality mobile application. In Lecture notes in computer science (pp. 489–499). https://doi.org/10.1007/978-3-031-06427-2_41.

6. Archana, R., & Jeevaraj, P. S. E. (2024). Deep learning models for digital image processing: a review. Artificial Intelligence Review, 57(1). https://doi.org/10.1007/s10462-023-10631-z.

7. Lu, L., Di, L., & Ye, Y. (2014). A Decision-Tree Classifier for Extracting Transparent Plastic-Mulched Landcover from Landsat-5 TM Images. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 7(11), 4548–4558. https://doi.org/10.1109/jstars.2014.2327226.

8. Wu, N. J. (2012). Efficient HIK SVM learning for image classification. IEEE Transactions on Image Processing, 21(10), 4442–4453. https://doi.org/10.1109/tip.2012.2207392.

9. Taherkhani, A. (2010). Recognizing Sorting Algorithms with the C4.5 Decision Tree Classifier. In IEEE 18th International Conference on Program Comprehension (pp. 72–75). https://doi.org/10.1109/icpc.2010.11.

10. Xu, N. Y., Sonka, M., McLennan, G., Guo, N. J., & Hoffman, E. (2006). MDCT-based 3-D texture classification of emphysema and early smoking related lung pathologies. IEEE Transactions on Medical Imaging, 25(4), 464–475. https://doi.org/10.1109/tmi.2006.870889.

11. Srensen, L., Shaker, S. B., & De Bruijne, M. (2010). Quantitative analysis of pulmonary emphysema using local binary patterns. IEEE Transactions on Medical Imaging, 29(2), 559–569. https://doi.org/10.1109/tmi.2009.2038575.

12. Ponnusamy, R., Sathyamoorthy, S., & Manikandan, K. (2017). A Review of Image Classification Approaches and Techniques. International Journal of Recent

Trends in Engineering and Research, 3(3), 1–5. https://doi.org/10.23883/ijrter.2017.3033.xts7z.

13. Pineda-Jaramillo, J. D. (2019). A review of Machine Learning (ML) algorithms used for modeling travel mode choice. DYNA, 86(211), 32–41. https://doi.org/10.15446/dyna.v86n211.79743.

14. Alnuaimi, A. F., & Albaldawi, T. H. (2024). An overview of machine learning classification techniques. BIO Web of Conferences, 97, 00133. https://doi.org/10.1051/bioconf/20249700133.

15. Medical Directory of Diseases and Medicines – Apps on Google Play. (2024). https://play.google.com/store/apps/details?id=ru.medical.spravochnik.

16. First aid kit. Accounting for medicines. – Apps on Google Play. (2024). https://play.google.com/store/apps/details?id=ru.decsoft.myaidkit.

17. Medication Control – Apps on Google Play. (2024). https://play.google.com/store/apps/details?id=ua.com.hitmax.liki.

18. My Medicine – Health Log. – Apps on Google Play (2024). https://play.google.com/store/apps/details?id=health.doctor.pill.my_medicine.

19. Medscape – Apps on Google Play. (2024). https://play.google.com/store/apps/details?id=com.medscape.android.

20. Medisafe Pill & Med Reminder – Apps on Google Play. (2024). https://play.google.com/store/apps/details?id=com.medisafe.android.client.

21. MyTherapy Pill Reminder – Apps on Google Play. (2024). https://play.google.com/store/apps/details?id=eu.smartpatient.mytherapy.

22. Medsbit Medication Tracker – Apps on Google Play. (2024). https://play.google.com/store/apps/details?id=all.pillreminder.medicationtracker.medsalarm.

23. Saha, S. (2023). A Comprehensive Guide to Convolutional Neural Networks — the ELI5 way. https://saturncloud.io/blog/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way/.

24. Li, H., Krček, M., & Perin, G. (2020). A comparison of weight initializers in Deep Learning-Based Side-Channel analysis. In Lecture notes in computer science (pp. 126–143). https://doi.org/10.1007/978-3-030-61638-0_8.

25. Narein, A. (2021). Inception V3 Model Architecture. https://iq.opengenus.org/inception-v3-model-architecture/.

26. Fabien, M. (2019). XCeption Model and Depthwise Separable Convolutions. https://maelfabien.github.io/deeplearning/xception/.

27. Datagen Tech. ResNet-50: The Basics and a Quick Tutorial. https://datagen.tech/guides/computer-vision/resnet-50/.

28. Badgujar, S. (2021). Creating MobileNetsV2 with TensorFlow from scratch. https://medium.com/analytics-vidhya/creating-mobilenetsv2-with-tensorflow-from-scratch-c85eb8605342.

29. Reda, M., Suwwan, R., Alkafri, S., Rashed, Y., & Shanableh, T. (2022). AgroAID: a mobile app system for visual classification of plant species and diseases using deep learning and TensorFlow Lite. Informatics, 9(3), 55. https://doi.org/10.3390/informatics9030055.

30. Vulli, A., Srinivasu, P. N., Sashank, M. S. K., Shafi, J., Choi, J., & Ijaz, M. F. (2022). Fine-Tuned DenseNET-169 for breast cancer metastasis prediction using FastAI and 1-Cycle Policy. Sensors, 22(8), 2988. https://doi.org/10.3390/s22082988.

31. Alshannaq, O., Alsayaydeh, J. A. J., Hammouda, M. B., Ali, M. F., Alkhashaab, M. A. R., Zainon, M., & Jaya, A. S. M. (2022). Particle swarm optimization algorithm to enhance the roughness of thin film in tin coatings. ARPN Journal of Engineering and Applied Sciences, 17(2), 186–193.

32. Oliinyk, A., Fedorchenko, I., Stepanenko, A., Rud, M., & Goncharenko, D. (2020). Implementation of evolutionary methods of solving the travelling salesman problem in a robotic warehouse. In Lecture notes on data engineering and communications technologies (pp. 263–292). https://doi.org/10.1007/978-3-030-43070-2_13.

33. Izonin, I., Tkachenko, R., Shakhovska, N., & Lotoshynska, N. (2021). The Additive Input-Doubling Method Based on the SVR with Nonlinear Kernels: Small Data Approach. Symmetry, 13(4), 612. https://doi.org/10.3390/sym13040612.

34. Syromiatnikov, A., & Weyns, D. (2014). A Journey through the Land of Model-View-Design Patterns. In 2014 IEEE/IFIP Conference on Software Architecture (WICSA) (pp. 21–30). https://doi.org/10.1109/wicsa.2014.13.

35.Franklin, R. (2022). AES vs. RSA Encryption: What Are the Differences? https://www.precisely.com/blog/data-security/aes-vs-rsa-encryption-differences.

36.Froehlich, A. (2021). What is ciphertext feedback (CFB)? https://www.techtarget.com/searchsecurity/definition/ciphertext-feedback.

37. Hammod, D. N., Al-Rawi, M., & Abdulah, H. S. (2016). An enhancement method based on modifying CFB mode for key generation in AES algorithm. Engineering and Technology Journal, 34(6B), 759–768. https://doi.org/10.30684/etj.34.6b.5.

38. Medium, Introduction to RSA. (2019). https://medium.com/@c0D3M/introduction-to-rsa-e8cb39af508e.

39. LinkedIn. (2024). How do you use AES and RSA together for hybrid encryption schemes? https://www.linkedin.com/advice/0/how-do-you-use-aes-rsa-together-hybrid-encryption-schemes.

40. Rudkovskyi, O. R., & Kirichek, G. G. (2020). Interaction support system of network applications. In 3rd Workshop for Young Scientists in Computer Science & Software Engineering (pp. 11–23).

41. Alshannaq, O., Alsayaydeh, J. A. J., Hammouda, M. B. A., Ali, M. F., Alkhashaab, M. A. R., Zainon, M., & Jaya, A. S. M. (2022). Particle swarm optimization algorithm to enhance the roughness of thin film in tin coatings. ARPN Journal of Engineering and Applied Sciences, 17(2), 186–193.

42. Alsayaydeh, J. A. J., Khang, A. W. Y., Indra, W. A., Shkarupylo, V., Hossain, A. K. M. Z., Saravanan, N., & Pusppanathan, J. B. (2019). Development of Vehicle Door Security using Smart Tag and Fingerprint System. International Journal of Engineering and Advanced Technology, 9(1), 3108–3114. https://doi.org/10.35940/ijeat.e7468.109119.

43. Alsayaydeh, J. A. J., Aziz, A., Rahman, A. I. A., Abbasi, M. I., & Khang, A. W. Y. (2021). Development of Programmable Home Security using GSM System for Early Prevention. ARPN Journal of Engineering and Applied Sciences, 16(1), 88–97.

44.Oliinyk, A., Fedorchenko, I., Donenko, V., Stepanenko, A., Korniienko, S., & Kharchenko, A. (2020). Development of an evolutionary optimization method for financial indicators of pharmacies. International Journal of Computing, 19(3), 449–463. https://doi.org/10.47839/ijc.19.3.1894.

НЕЙРОМЕРЕЖЕВА МОДЕЛЬ ДЛЯ ОПТИМІЗОВАНОГО КЕРУВАННЯ ЛІКАРСЬКИМИ ЗАСОБАМИ В УНІВЕРСАЛЬНІЙ АПТЕЧЦІ

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Анотація. *Було розроблено модифіковану модель згорткової нейронної мережі MediPackNet з точністю 92%, яка правильно розпізнала всі 5 тестових зображень лікарських засобів. Вона продемонструвала хороші результати на рівні 6 моделей, побудованих на основі відомих архітектур, а саме: InceptionV3, Xception, ResNet50V2, MobileNetV2, NASNetMobile та DenseNet169. Крім того, були реалізовані методи шифрування даних AES, RSA та їх комбінація. За результатами аналізу встановлено, що найефективнішим для розробленого програмного забезпечення є гібридне шифрування. Створено мобільний застосунок для обліку лікарських засобів універсальної аптечки, забезпечено його стабільну роботу та можливість для подальшого розвитку. Розроблений застосунок здатен суттєво полегшити процес управління запасами лікарських засобів, сприяє ефективнішому використанню медичних ресурсів і оптимізації закупівель. Крім того, можливість відстеження курсу лікування забезпечує точніше дотримання медичних рекомендацій і сприяє ефективнішому моніторингу стану здоров'я. Використання мобільного застосунку також має значний вплив на навколишнє середовище, оскільки зменшує кількість небезпечних відходів, пов'язаних із неналежним зберіганням і утилізацією прострочених лікарських засобів.*

Ключові слова: *облік, лікарські засоби, аптечка, паковання, розпізнавання , мобільний застосунок, .NET MAUI, Python.*