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Abstract. This study examines the current challenges in processing and analyzing medical images using machine learning techniques. Based on the Pediatric Chest X-ray Pneumonia dataset, a convolutional neural network (CNN) model was developed and evaluated for its ability to detect pneumonia. The results confirmed the high efficiency of deep learning in medical diagnostics.

Keywords: machine learning, CNN, pneumonia, X-ray, Classification Report, diagnostics.

Medical image processing and analysis play a critical role in enhancing diagnostic accuracy. In particular, identifying lung diseases such as pneumonia from chest X-ray images remains an important task. Pneumonia is a severe illness characterized by inflammation of lung tissue. Physicians frequently use chest X-rays to diagnose this condition. However, interpreting radiographic images is a complex process requiring skilled radiologists. In this context, machine learning, especially convolutional neural networks (CNNs), has emerged as a powerful tool to automate and expedite this task.

In the present study, we developed a system for detecting pediatric pneumonia using machine learning algorithms. An open-access medical image dataset was employed from the Kaggle platform, with preprocessing and data augmentation techniques applied to the images. The developed model demonstrated high accuracy in automatic classification of pneumonia cases [1].

The main objectives of the study are as follows:

- To design a system for the automatic detection of pneumonia in children;
- To improve classification accuracy using image preprocessing and augmentation;
- To evaluate the performance of the model on real medical datasets.

Medical imaging refers to a set of non-invasive techniques that visualize the internal structures and physiological processes of the human body or other living organisms. These technologies have become essential tools in modern medicine. They are widely used for diagnosis, treatment planning, surgical intervention, and treatment monitoring. Medical imaging allows healthcare professionals to examine internal organs without surgery, thereby improving patient safety and reducing the need for invasive procedures while enhancing the accuracy and reliability of clinical decisions.

Common types of medical imaging include X-ray radiography, computed tomography (CT), magnetic resonance imaging (MRI), ultrasound (US), as well as nuclear medicine techniques such as single-photon emission computed tomography (SPECT) and positron emission tomography (PET). Each method provides specific advantages. For instance, X-rays are effective for examining bone structures, while MRI offers detailed imaging of soft tissues, muscles, and nerves. CT enables high-precision analysis of internal organ morphology through layer-by-layer imaging [2].

Advanced technologies are also employed in the processing and interpretation of medical images. Multimodal fusion allows the integration of data from different imaging devices, while temporal fusion supports comparison of images taken at different times. These techniques are essential for tracking patient progress and forming accurate diagnoses. Methods such as 3D reconstruction from 2D images, volume rendering, and other visualization tools provide spatial insights into anatomical structures. Over recent years, the incorporation of artificial intelligence (AI) and machine learning (ML) technologies into medical imaging has revolutionized the field.

These approaches automate complex image analysis tasks, such as segmentation, classification, and anomaly detection, leading to faster and more accurate diagnoses [3]. Table 1 presents an overview of prominent machine learning algorithms and their respective applications within the domain of medical image analysis, illustrating the growing synergy between computational intelligence and medical diagnostics.

№	Algorithm	Application Area	Description
1	Convolutional Neural Networks (CNN)	Segmentation, classification, object detection	Used to isolate critical regions in medical images for disease recognition
2	Support Vector Machine (SVM)	Diagnosis, image classification	Accurately separates images into two or more categories
3	Random Forest	Feature detection, decision-making	Combines multiple decision trees to deliver robust results
4	Logistic Regression	Binary classification (e.g., disease/no disease)	Applied to yes/no decision scenarios
5	K-Nearest Neighbors (KNN)	Image similarity analysis	Suggests diagnosis by comparing a patient's image to similar samples
6	U-Net	Pixel-wise anatomical segmentation	Highly effective in precise segmentation tasks
7	Decision Tree	Rule-based diagnosis	Easy to interpret but limited generalization capability

Table 1: Applications of Machine Learning Algorithms in Medical Imaging

In our study, we focus on a specific type of medical image – X-ray scans. Using modern machine learning methods, models were developed to automatically identify anatomical structures. Image segmentation helps delineate organ boundaries, which is essential for further analysis and automated diagnosis. The integration of machine learning with medical imaging improves diagnostic speed and accuracy.

Model Development and Training

Several key stages were implemented during the model training process:

Data preparation: All training images were resized to a consistent 224x224 pixel format to ensure effective processing by the neural network.

Augmentation: Augmentation techniques, including rotation, scaling, and shifting, enhanced the model's adaptability to variations in the data.

Model training: The model was trained over 10 epochs. Accuracy and loss were monitored after each epoch. Post-training, the model was evaluated using the test dataset.

The study utilized the "Pediatric Chest X-ray Pneumonia" dataset from Kaggle, which includes both normal and pneumonia-labeled chest X-ray images of children [4]. The dataset was divided as follows:

- Train set: used for model training.
- Test set: used for performance evaluation.

Image preprocessing was conducted using the ImageDataGenerator library with techniques such as horizontal flipping, scaling, and shifting to increase model robustness.

A Convolutional Neural Network (CNN) was constructed as the neural network architecture. The model consisted of several layers, including Conv2D, MaxPooling2D, Flatten, Dense, and

Dropout layers. The ReLU activation function was applied in the intermediate layers, while a sigmoid activation function was used in the final layer due to the binary classification nature of the task.

During model compilation, the binary_crossentropy loss function and the Adam optimizer were selected. The training process was conducted for 10 epochs, with accuracy and loss metrics monitored to evaluate performance.

For model evaluation, data from the test set was utilized. Additionally, a Confusion Matrix, Classification Report, and AUC-ROC curve were generated to provide a comprehensive assessment of the model's effectiveness.

Preprocessing and augmentation procedures involved the following steps:

- Resizing images to 224x224 pixels to ensure uniform input dimensions across the dataset.
- Scaling pixel values to the range 0 to 1 to normalize input data for the neural network.

The augmentation methods applied included:

- Rotation - rotating images to enhance the model's robustness to orientation variations.
- Horizontal flipping - providing the model with different viewing angles.
- Zooming - allowing the model to recognize features at various scales.

CNN Model Architecture. A convolutional neural network (CNN) was implemented with the following architecture:

- Conv2D + MaxPooling2D (32 filters, 3x3): feature extraction from input images.
- Conv2D + MaxPooling2D (64 filters, 3x3): identification of additional features.
- Conv2D + MaxPooling2D (128 filters, 3x3): analysis of high-level image features.
- Conv2D + MaxPooling2D (256 filters, 3x3): extraction of deeper abstract features.
- Flatten + Dense (128 neurons, ReLU): conversion to a fully connected layer.
- Dropout (0.5): reduces overfitting.
- Output layer (Sigmoid): performs binary classification to predict either "Normal" or "Pneumonia".

The model was compiled using the Adam optimizer and binary cross-entropy as the loss function. Training was conducted for 10 epochs.

Evaluation and Results. Prediction Output: The model produced a binary classification output, as shown in Figure 1, correctly identifying pneumonia.



Fig 1: software model forecast

Performance Metrics:

Maximum accuracy: 87.01

Loss: 0.3669

Error Analysis: The performance evaluation involved Confusion Matrix and Classification Report. Despite a few false positives (normal labeled as pneumonia) and false negatives (pneumonia labeled as normal), the overall accuracy remained high.

AUC-ROC Curve: The model's ability to distinguish between "Normal" and "Pneumonia" classes was further validated using the AUC-ROC curve. The AUC score of 0.91 indicated excellent classification performance.

Discussion and Future Work. This study confirms the feasibility of using deep learning algorithms to detect pneumonia from pediatric chest X-ray images. However, several aspects can be improved:

- Larger dataset: Expanding the dataset and retraining the model could enhance its generalizability and accuracy.
- Model versatility: Developing models for other medical conditions such as bronchitis or tuberculosis could broaden clinical applications.
- Interpretability: Integrating interpretation tools like Grad-CAM may help visualize features that influenced the model's decision-making process.

Conclusion. A deep learning-based model was developed for pneumonia detection using pediatric chest X-ray images. The study demonstrated that preprocessing, augmentation, and classification yielded high accuracy. The findings confirm the significant potential of machine learning in medical diagnostics. The future implementation of such systems in clinical practice could enhance diagnostic quality and treatment outcomes.

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ARTIFICIAL INTELLIGENCE FOR SOFTWARE DEVELOPMENT WITH ECONOMIC SECURITY IN MIND

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In the modern world, where technologies are rapidly developing and information flows are increasing exponentially, software is becoming a critical component in the functioning of both private businesses and government agencies. At the same time, the growth in complexity and scale of software systems inevitably entails risks not only of a technical but also of an economic nature. Errors in the code, vulnerabilities in the architecture, inefficient allocation of resources - all this can lead to significant financial losses, and in some cases even to the undermining of trust in the company or government body.

Modern trends in digital transformation require not only accelerated development of software products, but also ensuring their resilience to economic threats: losses from cyberattacks, inefficient use of resources, costs of fixing errors. One of the promising tools for solving these problems is the use of artificial intelligence at all stages of the software life cycle [1].

Economic software security in this context means minimizing the financial risks associated with the development, implementation and operation of IT systems. The emergence and rapid development of artificial intelligence (AI) technologies offers new tools for solving these problems. AI can not only automate routine operations, but also provide intelligent analysis of source code, predict possible failures and optimize business logic from a cost perspective.

Economic security in information systems is not only protection against squirrel web, but also a broader concept that includes the sustainability of business processes, predictability of costs and reduction of the probability of losses due to technological errors. From the point of view of software engineering, the following key aspects of economic security can be distinguished:

- Optimization of software life cycle costs (development, testing, implementation, maintenance);
- Resilience to failures, attacks, and invalid data;
- Minimizing technology debt and controlling architecture quality;
- Increase development efficiency through automation and intelligence.