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Automated Radiograph Analysis for Pneumonia Detection in Healthcare Access

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Abstract
Pneumonia affects people across different age categories and is recognized as a serious condition impacting the respiratory system. Early diagnosis of pneumonia is crucial in order to lower the complications and enhance the success rates of cure. Chest X-ray imaging has been commonly employed for the diagnosis of pneumonia. Manual examination of chest X-ray images requires significant time and depends largely on the presence of trained radiology experts. This work proposes system for automatically detecting pneumonia from the chest X-rays using deep learning model. A Convolutional Neural Network (CNN) is trained to classify a chest X ray as Normal and Pneumonia. Methods such as resizing, normalizing, and performing data augmentation on images are used to optimize and increase the accuracy of results. The system also generates a level of confidence for each output. A web application is created to facilitate users in uploading their chest X-rays, and doctors can check and validate results. Experimental results verify a higher accuracy and supremacy of the proposed CNN method compared to a CNN-RNN combined model. The proposed system increases efficiency and helps doctors in diagnosing pneumonia cases.

Keywords: *Pneumonia Detection, Chest X-ray, Deep Learning, CNN, Medical Image Classification, Computer-Aided Diagnosis*

1. Introduction

Pneumonia refers to a serious lung infection that results in inflammation of the alveoli in the lungs, hence causing respiratory distress. In fact, it has been considered as one of the leading causes of mortality, especially among young children, the aged, and those with weakened body immunity [1], [6]. According to medical reports, pneumonia continues to cause significant mortality [6], especially due to delayed diagnosis in developing nations. The primary method employed for the detection of a pneumonia is chest X-ray imaging [7]. Specialists analyze the images of the X-rays to detect unusual patterns that might resemble the cloudy areas and opacities in lungs. Nevertheless, the method is subject to the limitations of human detection and the expertise and availability of a specialist are a major issue in rural hospitals and places where resources are a problem. Specialists may not be available on a daily basis even in urban hospitals and might lead to specialist fatigue due to a high number of images to observe. Machine learning and deep learning approaches have been widely applied in the task of detecting pneumonia. The earlier solutions involved traditional image analysis algorithms and feature design, which were expertise-dependent and performed poorly on challenging datasets [2], [3]. Such solutions lacked good generalization capabilities over images of different qualities and patient presentations.

2. Related Work

Recent works have employed deep learning models and CNN-based architectures identifying pneumonia in an automated manner. Transfer learning approaches have been applied by utilizing pre-trained architectures including VGG16, ResNet50, and

MobileNet [8], [10] to enhance the accuracy and speed of the training processes. Some works incorporated the attention mechanism to highlight the regions of the lungs [1], [4] that were infected. Though the works were accurate, most of them were standalone classifiers and did not integrate detection into the actual clinical practice system. Further, most developed models lack doctor validation and interaction functionality. This makes it difficult to adopt them in real life because they are not transparent and are not clinically validated [9]. This serves as an indication that an AI model that can detect pneumonia and has ease of-use and doctor verification capabilities is important.

2.1.Problem Statement

Traditionally, pneumonia is diagnosed by doctors through direct visual inspection of chest X-ray images [7]. Since radiologists are required to review many X -ray scans each day, the procedure becomes time-consuming and error-prone. In many rural hospitals, specialist doctors are not always available, which often results in delayed diagnosis and improper treatment. The existing automated solutions are either expensive in terms of infrastructure or unreliable and opaque. A few systems provide predictions only, without confidence scores or expert validation. Hence, this calls for the development of a low-cost, highly accurate, user-friendly system that is capable of identifying pneumonia from chest X-ray images in an automated manner.

3. Proposed System

The proposed system is an automatic pneumonia detection system based on deep learning, which analyzes chest X-rays [2], [5]. The system uses a CNN model to classify images into Normal and Pneumonia categories. Various image processing methods are used to optimize image quality and efficiency. One of the important components of the system is the inclusion of an online interface. The system allows the upload of chest X-ray images and the generation of instant results. The system also allows the doctors to have independent access to the results and to check the predictions for accuracy and to provide their own confirmation.

3.1.1. Objectives

- To preprocess the dataset using standard image processing techniques such as resizing, normalization, and data augmentation to improve model robustness.
- To develop a pneumonia detection system using deep learning techniques, including Convolutional Neural Networks (CNNs) and hybrid CNN+RNN models, for identifying pneumonia-related patterns in chest X-ray images.
- To evaluate the performance of the developed models using performance metrics such as accuracy, precision, recall, and F1 score.
- To design and implement a user-friendly web interface that accepts chest X-ray images and predicts whether they are normal or pneumonia.

3.2. Methodology

Data Collection: The process starts with the collection of chest X-ray images which serve as the primary source of data throughout the system. The images of the chests of pneumonia-affected persons can be obtained from a publicly available source of images [2], [6], which include normal as well as pneumonia images. The collected X-ray images form the foundation for all further processing steps. Data Preprocessing: After completing the data collection process, chest radiographic images go through a preprocess phase. At this phase, noisy and blurry areas in the images that are irrelevant for analysis are eliminated or diminished. This leaves the analysis phase with just the useful areas in the lung images. The images are then converted to a standard size and normalized. Additionally, augmentation methods such as image rotation, zoom variation, and flipping are applied. The dataset is then separated into training and testing sets using a 70:30 ratio. Feature Extraction: After preprocessing step, the next step is the extraction of features through deep learning algorithms. In this step, the system extracts prominent features like texture and opacity [3], [4] areas within the lungs and structural patterns which might show the existence of pneumonia. These features are very essential for determining normal lungs and pneumonia-infected lungs. Model Selection: Various algorithms were evaluated during

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experimentation, and the best performing model out of them had to be considered. In the proposed project work, the model that has been considered for experimentation is the Convolutional Neural Network model because it performs with higher accuracy for the detection of pneumonia in the chest X-ray images. Prediction and Analysis: The trained CNN architecture can then be utilized for classifying new chest X-ray images into either the Normal class or the Pneumonia class on the basis of the features obtained. The architecture provides probability outputs for both classes with the use of the Softmax activation function [9]. The metrics analysis can be utilized for checking the reliability of the outputs. User Interface: To make the system useful for practical applications, the learned model has been incorporated into web-based interface developed with streamlit. The user has the capability to upload chest X-ray images and receive real-time results. The output displays the predicted class along with the confidence score. The doctor would be able to make the necessary judgments. Shows in Figure1.

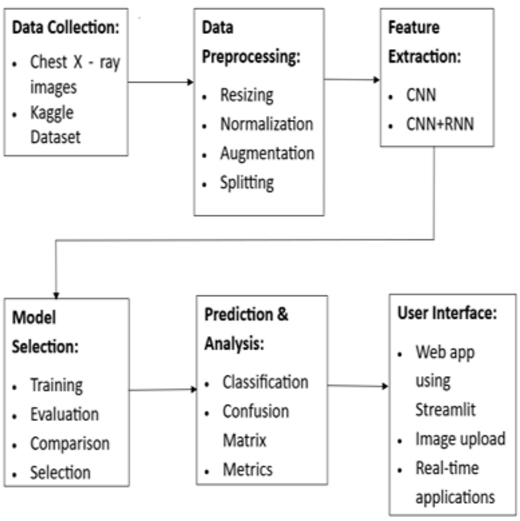

Figure 1. Methodology

4. Dataset Description

To evaluate the developed model, a widely used public dataset known as Chest X-ray Images - Pneumonia sourced from the Kaggle platform is used [2], [6]. The dataset is widely used in existing research related to pneumonia detection and possesses correct ground truth values for both normal and pneumonia-infected chest images. The dataset is composed of 8,860 chest X-ray images. Images are distributed in two classes: Normal and Pneumonia. These images are real cases with variation in resolution, contrast, and noise; thus, ideal for training the system to learn generalized features that could work in realistic applications of medical image processing. The dataset is organized into training and testing sets with a 70:30 distribution for the experiment. The training dataset makes use of image rotation, flipping, and zooming to be able to overcome overfitting. The images are all normalized to be able to introduce robustness to the model. This dataset can be seen as an effective source for testing the proposed system for detection of pneumonia.

4.1. Architecture

The architecture of the proposed pneumonia detection system is designed to support both users and doctors through a structured and interactive workflow. The system integrates deep learning based image analysis with a web interface to enable automated diagnosis and expert validation.

- User Workflow: To verify their identity, users first register for an account or access the system with their login information. After being verified, they use the web interface to upload a chest X-ray picture for assessment. In order to ascertain whether or not pneumonia is present, the CNN model processes the submitted image as the system's input. Important lung-related characteristics are extracted and examined during this procedure to ensure precise classification. The user is then shown the diagnosis outcome on the interface. The uploaded image and the prediction result can be kept in the system database for later physician review if necessary.
- Doctor Workflow: The Doctor Login module allows authorized medical professionals to securely access the system. After logging in,

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the doctor is shown a dashboard with a list of patients, their submitted chest X-ray images, and the predicted outcomes of the CNN model. Doctors are able to add diagnosis notes to a patient record based on their medical evaluation. Observations, suggestions, or confirmation may be included in these notes. After the doctor has completed reviewing the data, the updated patient record is saved in the database for later use.

- Data Storage and Flow: All user data, uploaded X-ray images, prediction results, and doctor diagnosis notes are stored securely. This ensures proper record management and allows follow-up analysis when required. The interaction between the user module and doctor module ensures both automated analysis and expert validation, improving reliability and clinical usefulness of the system

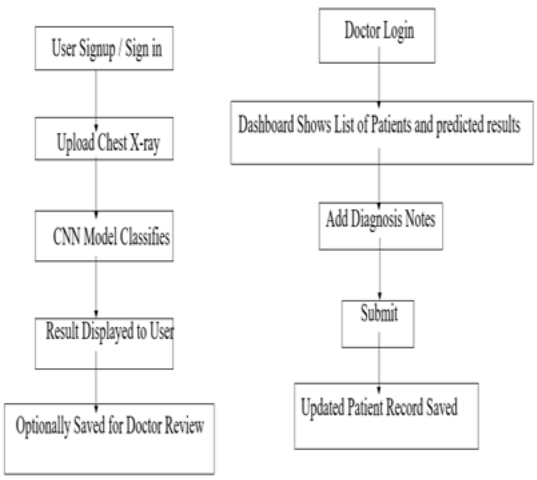

Figure 2. **Architecture of the System**

5. Description Of Modules

Data Gathering and Processing: This module helps in getting the chest X-ray images collected from patients. All the obtained images undergo preprocessing tasks like resizing them into a fix size, normalizing the pixel intensity, as well as performing data augmentations like rotation, zooming, and flip transformations on them. All these activities help ensure that the model gets properly processed data to obtain important features [6].

Feature Extraction: Module Finally, the preprocessing phase follows the extraction of key features for the images using a customized CNN neural network architecture built with Keras. The convolutions detect edges, textures, and patterns in the lungs, which allows the features to be important enough for distinguishing between the Normal and the Pneumonia class [5], [10].

Feature Analysis Module**:** The features so far extracted are processed for overfitting using dense layers and dropout layers. A Softmax activation function is applied for the final prediction, which represents the class probabilities or the confidence level for each class [9].

Recognition & Classification: In this module, the class with the highest score is identified. If the score is above the threshold level, then the X-ray is identified. If the score is above the threshold level, then the X-ray is classified as Normal or Pneumonia. But in the case of less confidence level, the classification can be made as uncertain.

Frontend and Backend: The system employs the use of Streamlit to create an interface that enables the user to submit chest X-ray images for prediction generation. Streamlit is very efficient in the handling of requests as well as the output presentation. In addition, the interface can be improved by the use of HTML, CSS, or JavaScript coding languages.

Output and Decision: After obtaining the probabilities of the prediction, they are sorted from highest to lowest based on their probability. The class with the highest probability is then picked as the final diagnosis, and the confidence level at which the system is sure about its diagnosis is shown.

5.1.Implementation

The pneumonia detection system was built using a variety of tools and technologies strive to make it fast, efficient, and also user-friendly.

- Python: All coding, related to both the AI model and the backend, was performed in Python. It is easy to use and has great libraries assisting in machine learning and web applications.[11]

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- Convolutional Neural Network (CNN): A neural network-based learning model, features of interest from X-ray images, and learns automatically, for instance, patterns in the lungs. It can classify images as Normal or Pneumonia. The most common use of CNNs is to perform very well in image-related tasks because they can detect shapes, edges, and textures very efficiently [1], [3], [10],[12].
- Recurrent Neural Network (RNN): RNNs are designed to understand sequences or patterns over time. They have been employed on text data, speech, and time-series data. The work discussed here involved the use of RNNs to check whether the analysis of patterns sequentially classification [8]. improve image [13].
- Hybrid CNN-RNN: It is the hybrid model that merges the strengths of both CNN and RNN; CNN first extracts features from images, while afterwards, RNN analyzes the patterns in those features. Although this approach can capture more complex information, experimental results showed that the standalone CNN model performed better for pneumonia detection [8], [10],[14].
- VS Code (Visual Studio Code): This is a powerful and intuitive code editor for use for to write, test, and debug Python scripts. It allows extensions for deep learning, which makes it convenient for the development and management of the pneumonia diagnosis system.
- TensorFlow / Keras: They were utilized as a powerful tool for building, training, and evaluating CNN and RNN models and also simplify the process of deep learning model development.
- Streamlit: A toolkit for building a web application that allows users to submit X-ray images and receive real-time prediction results.
- SQLite Database: SQLite is a light database designed to hold information of users along with prediction information records, doctors, and patients to be able to obtain their results[15].

All these tools and technologies combined have enabled the development of a system that has the ability to train a reliable artificial intelligence model, make accurate predictions, and offer a simple means interface for real-world applications.

6. Results And Discussion

6.1. Results of Each Module

This web application allows patients to upload and analyze their chest X-rays for pneumonia detection. Doctors can review the AI-generated results and provide expert feedback. Each page is designed to be simple, clear, and focused on accurate results.

6.2. Home Page

- Displays the project name and provides Sign Up and Login options.
- Explains the Process: Secure Upload → AI Analysis → Expert Review.
- Highlights advantages: instant results, research-backed accuracy, expert access, global availability.

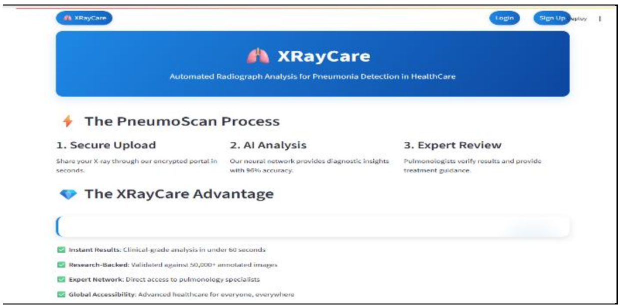

Figure 3. Home Page Interface

6.3.Login Page

- Secure login for registered users with Username and Password.

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- Option to create a new account

Figure 4 Login Page

6.4.Sign-Up Page

- Collects Full Name, Email, Username, Password, and Profile Type (Patient, Doctor).
- Allows new users to register securely.

Figure 5 Sign-Up Page

6.5. Patient Dashboard

- Shows Health Timeline and option to upload new chest X-rays.
- Supports drag-and-drop or file browsing for images.
- AI provides instant analysis of uploaded scans.

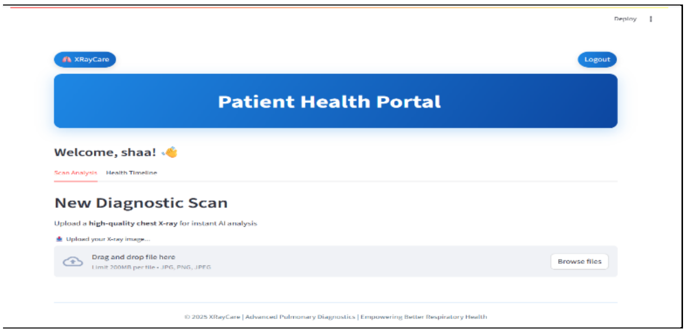

Figure 6. Diagnostic Scan Page

6.6.Diagnostic Scan Page

- Displays uploaded image and analysis result.
- Shows Diagnostic Confidence and recommended actions (specialist review, follow-ups).

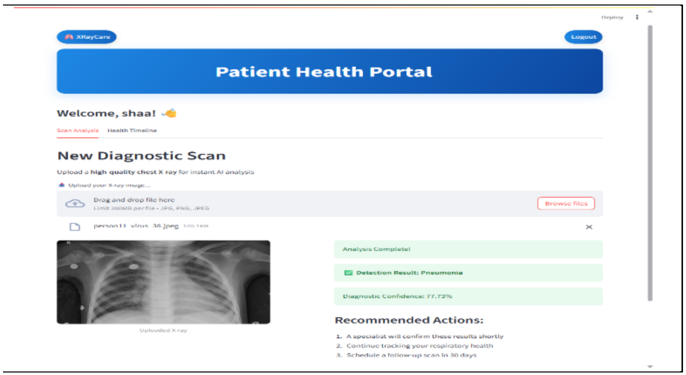

Figure 7 Diagnostic Scan

6.7.Health Timeline / History Page

- Displays past scans with date, diagnosis, and confidence.
- Shows specialist assessments and treatment guidance if needed

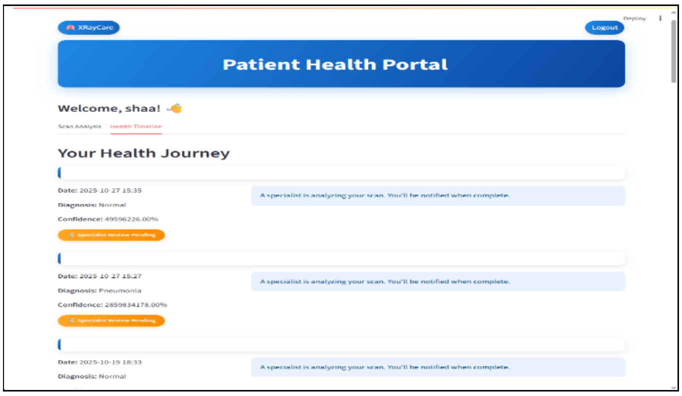

Figure 8.Health Timeline Page

6.8.Specialist Dashboard

- Shows priority cases awaiting review.

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- Displays AI assessment, confidence, and patient details.
- Specialists can submit clinical notes and confirm diagnosis.

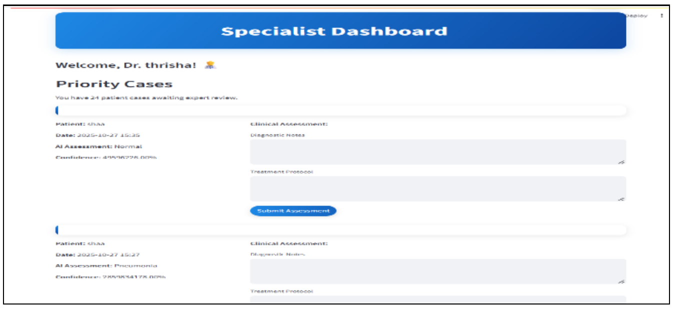

Figure 9.Doctor Dashboard

6.9.Comparative Analysis of Results

Two models, CNN and CNN + RNN, were tested to detect pneumonia from chest X-ray images. Their performances were compared using accuracy, precision, recall, and F1-score.

Table 1 Performance Measures

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN	96.2	95.5	96.8	96.1
CNN + RNN	94.7	94.2	94.9	94.5

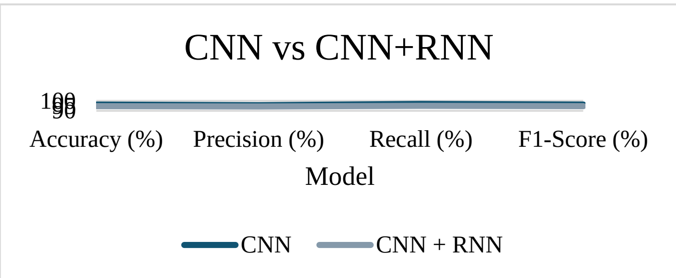

FIGURE 9 Performance Comparison of Models

From the results, it is observed that CNN performed slightly better than the hybrid CNN+RNN model. Therefore, the CNN model was selected as the final model for this project.

Conclusion

The proposed work provides an automated pneumonia detection solution on based deep learning techniques applied to chest X-ray images The CNN approach effectively analyzes X-ray images and accurately classifies them into Normal or Pneumonia categories. The web-based interface and physician verification increase the usability and accuracy of the method. The developed system reduces the diagnosis period, effort, and work done manually, as well as aids the doctors in decision-making. Since early screening of pneumonia, especially in developing countries, has been made possible by this system, this shows how AI can be applied in the healthcare sector. This work shows how deep learning helps enhance medical diagnosis and, in turn, patient care [6], [10].

Journal reference style:

[1].An, W., Chen, J., & Shao, W. (2024). A deep convolutional neural network for pneumonia detection in X-ray images using attention ensemble. *Diagnostics*, 14(4), 390. doi:10.3390/diagnostics14040390.

[2]. Asnake, A., & Salau, A. (2024). X-ray image-based pneumonia detection and classification using deep learning. Multimedia Tools and Applications, 83(21), 60789–60807. doi:10.1007/s11042-024-17060-3.

[3].Binte Rashid, T., Ahmed, M., Islam, M., & Rahman, S. (2025). An enhanced deep learning framework for pneumonia detection in chest X-rays. SN Computer Science, 6, 472. doi:10.1007/s42979-025-02877-1.

[4].Colin, N., & Surantha, N. (2025). Interpretable deep learning for pneumonia detection using chest X-ray images. Information, 16(1), 53. doi:10.3390/info16010053.

[5]. Haritha, B., & Lavanya, P. (2022). Analysis of chest X-ray images using deep learning techniques. Proceedings of the 4th International Conference on Computational Intelligence and Smart Systems (ICCISS), 88–95. doi:10.1109/ICCISS55157.2022.9781383.

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Page No: 2393-2400
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0321

[6]. Kim, J., et al. (2021). Deep learning computer-aided detection system for pneumonia in febrile neutropenia patients: A diagnostic cohort study. BMC Pulmonary Medicine, 21, 406. doi:10.1186/s12890-021-01666-9.

[7]. Ioannou, Z., Kambaroudis, A., & Koutroulis, G. (2012). Reading and interpretation of chest X-ray in adults with community-acquired pneumonia. European Radiology, 22, 1–10. doi:10.1007/s00330-011-2265-6.

[8]. Prasanna, K., Kumar Raju, S. R., & Krishna, J. (2024). Effect of learning rate on the performance of VGG-16 in prediction of cardiomegaly from chest X-ray images. Recent Advances in Materials Manufacturing and Machine Learning, 836–844. doi:10.1007/978-3-031-53023-7_73.

[9]. Sanida. (2024). Optimizing lung condition categorization through a deep learning approach. Algorithms, 17(3), 109. doi:10.3390/a17030109.

[10]. Singh, M., Kumar, M., Kumar, A., Verma, B. K., & Shitharth, S. (2024). Efficient pneumonia detection using vision transformers on chest X-rays. Scientific Reports, 14, 3273. doi:10.1038/s41598-024-52703-2.

[11]. Kabir, M. A., Ahmed, F., Islam, M. M., & Ahmed, M. R. (2024). Python for data analytics: A systematic literature review of tools, techniques, and applications. AJSTEME, 4(4). doi: 10.69593/ajsteme.v4i04.146.

[12]. Raj, R., & Kos, A. (2025). An extensive study of convolutional neural networks: Applications in computer vision for improved robotics perceptions. Sensors, 25(4), 1033. doi: 10.3390/s25041033.

[13]. Sherstinsky, A. (2020). Fundamentals of recurrent neural network (RNN) and long short-term memory (LSTM) network. Physica D: Nonlinear Phenomena, 404, 132306. doi: 10.1016/j.physd.2019.132306.

[14]. Donahue, J., Hendricks, L. A., Guadarrama, S., Rohrbach, M., Venugopalan, S., Saenko, K., & Darrell, T. (2015). Long-term recurrent convolutional networks for visual recognition and description. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2625–2634. doi: 10.1109/CVPR.2015.7298878.

[15]. Hipp, D. R. (2020). SQLite. ACM Transactions on Database Systems, 45(3), 1–38. doi: 10.1145/3390176.