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WEB-BASED INFORMATION TECHNOLOGY FOR CLASSIFYING AND INTERPRETING EARLY PNEUMONIA BASED ON FINE-TUNED CONVOLUTIONAL NEURAL NETWORK

There have been rapid development and application of computer methods and information systems in digital medical diagnosis in recent years. However, although computer methods of medical imaging have proven helpful in diagnosing lung disease, for detecting early pneumonia on chest X-rays, the problem of cooperation between professional radiologists and specialists in computer science remains urgent. Thus, to address this issue, we propose information technology that medical professionals can employ to detect pneumonia on chest X-rays and interpret the results of the digital diagnosis. The technology is presented as a web-oriented system with an available and intuitive user interface. The information system contains three primary components: a module for disease prediction based on a classification model, a module responsible for hyperparameter tuning of the model, and a module for interpreting the diagnosis results. In combination, these three modules form a feasible tool to facilitate medical research in radiology. Moreover, a web-based system with a local server allows storing personal patient data on the user's computing device, as all calculations are performed locally.

Keywords: information technology, web-system, pneumonia, chest X-ray, convolutional neural network, hyperparameter fine-tuning, class activation maps

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ВЕБ-ОРІЄНТОВАНА ІНФОРМАЦІЙНА ТЕХНОЛОГІЯ ДЛЯ КЛАСИФІКУВАННЯ ТА ІНТЕПРЕТУВАННЯ РАННЬОЇ ПНЕВМОНІЇ НА ОСНОВІ НАЛАШТОВАНОЇ ЗГОРТКОВОЇ НЕЙРОННОЇ МЕРЕЖІ

Упродовж останніх років, у сфері цифрового медичного діагностування спостерігається стрімкий розвиток та повсюдне застосування комп'ютерних методів та інформаційних систем для аналізу медичних зображень. Проте, хоча комп'ютерні засоби оброблення медичних зображень довели свою практичну користь у завданнях діагностування легеневих захворювань, зокрема, для виявлення ранньої пневмонії на рентгенівських зображеннях, актуальною залишається задача синергії досвіду професійних радіологів та фахівців комп'ютерних наук. Тому для розв'язання нагальної задачі цифрового діагностування в роботі пропонується інформаційна технологія, яку спеціалісти медичної сфери можуть використовувати для виявлення пневмонії на рентгенівських зображеннях грудей та інтерпретування результатів діагностування. Технологія представлена у вигляді веборієнтованої інформаційної системи з оглядом на доступність та зручність користувацького інтерфейсу. Водночас інформаційна система складається з трьох основних модулів. Перший модуль спрямований на прогнозування наявності захворювання; для цього використано модель класифікації на основі згорткової нейронної мережі із трьома згортковими шарами та операцією розширеної згортки. Другий модуль відповідає за налаштування гіперпараметрів навчання нейронної мережі на основі модифікованого еволюційного алгоритму. Третій модуль призначений для відображення та інтерпретування результатів діагностування пневмонії на рентгенівських зображеннях із використанням технології мап активації класів. У поєднанні ці три модулі утворюють робочий інструмент для допомоги медичним дослідникам та професійним рентгенологам. Варто також зауважити, що веборієнтованість системи із локальним сервером дає змогу зберігати персональні дані пацієнта на обчислювальному пристрої користувача, оскільки всі обчислення відбуваються локально.

Ключові слова: інформаційна технологія, веб-система, пневмонія, рентгенограма, згорткова нейронна мережа, точне налаштування гіперпараметрів, мапи активації класів

Introduction

In recent decades, referral systems based on computer-assisted diagnosis have been used with varying degrees of success to improve health care. Such systems are usually based on the diverse machine learning (ML) approaches [1] and computer vision (CV) methods [2]. However, computer diagnostics technologies have still been in the research and preliminary implementation stages. There are many barriers to using computer-based information technology on an ongoing basis, namely the uncertainty of business models, lack of understanding of artificial intelligence (AI) in healthcare facilities, processing and storage of patients' data, data access problems, legal barriers, and more. The problems mentioned above remain a cornerstone in taxing collaboration between AI researchers and physicians who will use these technologies in clinical practice.

Related works

The existing platforms for developing AI algorithms to analyze medical images are predominantly not focused on applications in the medical field and have limited support for clinical trials. For example, platforms such as TensorFlow [3], PyTorch [4], and ONNX [5] are recognized deep learning (DL) libraries that allow creating complex DL models yet do not provide medical imaging functionality. Other instruments like NiftyNet [6] and MONAI [7] allow comprehensive processing of various medical images without a straightforward and user-friendly graphical interface. The lack of a convenient interface deters professional radiologists from using advanced software applications aimed at software professionals.

At the same time, several successful solutions for the analysis of medical images have also been developed over the last decade. There are many software tools freely available that can be successfully applied to narrowly specialized practical tasks in digital medical diagnostics, i.e., image classification (e.g., Tensor networks [8]), segmentation (e.g., MIScnn [9]), and visualization (e.g., mrivis [10]). However, these tools are aimed primarily at computer scientists, but not by medical researchers, including radiologists. Moreover, they do not provide a convenient user interface that can allow easy use in a short time. Thus, there is an urgent need to develop and implement InfoTech with a straightforward user interface that would allow effective clinical research in medical imaging.

Problem statement

The presented work describes a feasible prototype of information technology (InfoTech) that can be used to detect pneumonia on chest X-rays. The conceptual scheme of the proposed InfoTech was firstly described in our previous work [11]. In this study, we propose the technology in the form of a web-based information recommendation system that is aimed to process an X-ray image to confirm the diagnosis of pneumonia and pre-interpret the results of the diagnosis.

Within the study, the authors aim to fulfill the following objectives to achieve the main goal.

1. The ML model should be presented with a convenient and accessible interface.
2. The web application must ensure openness and clarity of calculations for the typical user.
3. The medical solutions are needed to be scaled without incurring enormous server costs.

The presented InfoTech contains three primary components: a module for disease prediction based on a classification model, a module responsible for hyperparameter tuning of the model, and a module for interpreting the diagnosis results. Together, these parts form a complete tool to help medical researchers and professional radiologists.

The framework of the information technology

Our InfoTech is based on three primary aspects: pneumonia prediction, results explanation, and efficient computation. The schematic framework of the proposed InfoTech is illustrated in fig. 1.

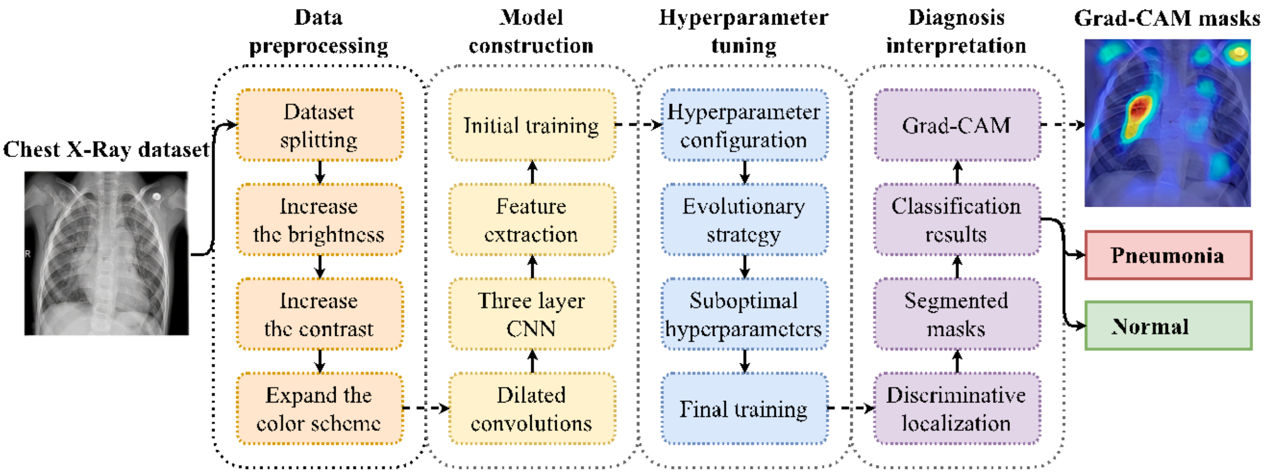


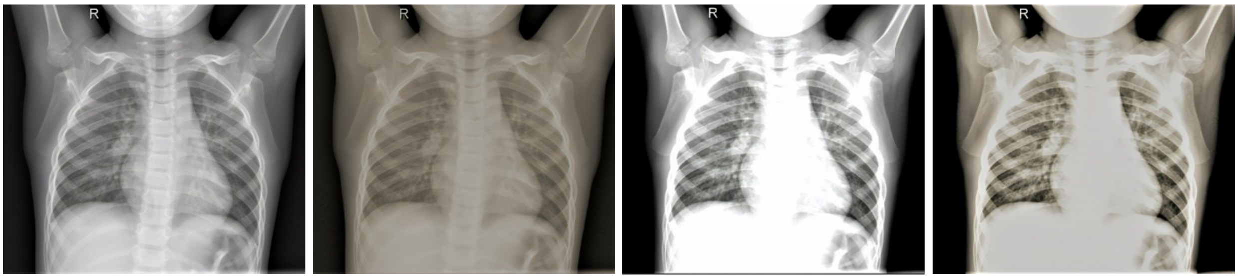
Fig. 1. The schematic framework of the proposed information technology.

According to the analysis of the related research, a particular type of artificial neural network (ANN) called convolutional neural network (CNN) has been considered the most prominent feature extractor [12]; consequently, a modified CNN was chosen as the classification model for the disease prediction. Explaining the prediction and interpreting classification results are crucial for any recommendation system in clinical diagnosis. So, the targeted module responsible for the interpretation was added to the technology. Finally, computational constraints are commonly an acute technical challenge while processing DL models. Thus, our system is based on the cooperation of TensorFlow.js [3] and ONNX, while the CNN model is trained in PyTorch. This stack was converted to work efficiently in the browser using WebGL.

Pneumonia detection

Dataset. In this work, we utilized the CheXpert dataset [13] to evaluate the classification model experimentally. The whole dataset comprises 3458 chest X-ray images of 320 × 320 pixels excluded from 524 patients. The radiographs were labeled as two targeted categories: normal and pneumonia. Also, CheXpert is divided into train, test, and validation samples, each containing 70%, 20%, and 10% of all samples, respectively.

Data preprocessing. Several color modifications were applied to all images of the CheXpert dataset to ensure good visibility of pneumonia features in the chest X-rays. First, the radiographs were illuminated to augment their brightness by parsing their pixels and then increasing the respective values of Red, Green, and Blue (RGB) by an absolute constant. Second, the images' contrast was also increased to make the borders more continuous and some areas more noticeable. Thirds, the images' color scheme was expanded by computing the average RGB values for each image. These values were multiplied by the calculated average to receive a color version of the image. Overall, the images created in this way allow highlighting the details on the surface so that the extractor can better identify any features and differences from the image with healthy lungs. The version of image preprocessing is presented in fig. 2.



a) b) c) d)

Fig. 2. An X-ray sample at different preprocessing stages: a) the original one; b) with modified lightning; c) with increased contrast; d) the final version of the colorized X-ray image.

Moreover, to enhance the generalization capacity of the model, a few data augmentation techniques, i.e., random rotation, translation, and scaling, were applied to all images.

Model. In this work, we employed a feature extractor as a hand-made CNN from our previous study [14]. Fig. 3 depicts the scheme of the presented CNN architecture.

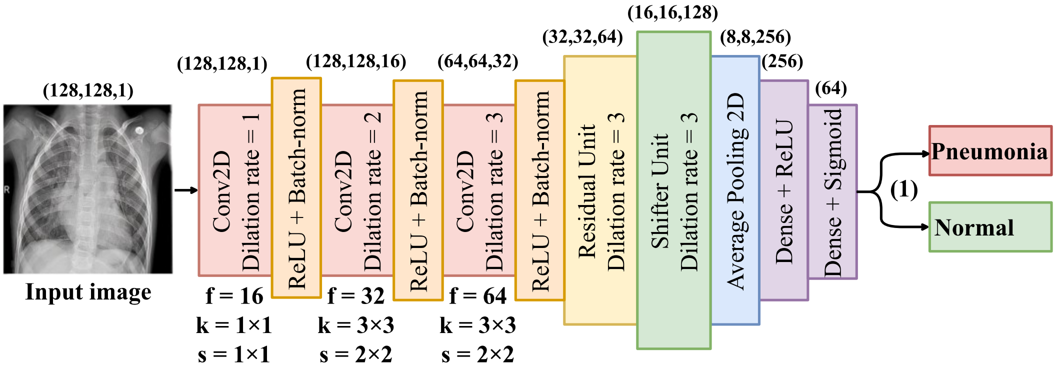


Fig. 3. The schematic representation of the utilized model [14].

From fig. 3, the CNN architecture here comprises three convolutional layers with dilated operations followed by ReLU activation functions and batch normalization operations after each layer. There are two specific convolutional operations called residual and shifter units, which successively pass into the averaged pooling layer and two dense (fully connected) layers. Our CNN ends with the sigmoid function as the last classification layer. It should be noted that dilated convolutions with different dilated rates were employed to detect and analyze visual deviations on the radiograph in convolutional layers to preserve the radiograph's receptive fields' spatial features. The network was trained with an Adam optimizer to minimize the cross-entropy loss function. The proposed architecture provides minimal loses of objects' spatial information due to dilated operations while ensuring low computational costs.

Tuning of convolutional neural network

This module of InfoTech processes the algorithm of tuning CNN's training hyperparameters. Here, we consider training hyperparameter tuning a global optimization task of searching a D-dimensional hyperparameter setting λ that ensures minimum loss function L with learned weights w. The suboptimal set λ can be obtained by applying the optimization function as

$$\begin{gathered}\min_{\lambda \subseteq \boldsymbol{R}^D}\left\{L_{val}\left(\lambda_{opt}, w^*, D_{val}\right)\right\},\\ w^* \in \arg\min_{w \in \mathbf{W}}\left\{L_{train}\left(\lambda, w, D_{train}\right)\right\},\\ \lambda^* \in \arg\min_{\lambda \in \boldsymbol{\Lambda}}\left\{L_{val}\left(\lambda, w, D_{val}, D_{train}\right)\right\},\end{gathered} \tag{1}$$

where L_{val} and L_{train} are validation and training loss functions, respectively, D_{val} and D_{train} stand for validation and training datasets, respectively, w^* and λ^* are the suboptimal set of weights and training hyperparameters.

Training hyperparameters has a significant impact on the performance of any CNN model, including our three-layer CNN from fig. 3. Therefore, to boost the network's training and ensure its good convergence on the validation dataset, we applied a surrogate-assisted evolutionary strategy [15] to tune CNN's training hyperparameters. The evolutionary algorithm can automatically find a competitive hyperparameter configuration rather than a manual search method with relatively low computational cost. The algorithm of the evolutionary strategy is described in fig. 4.

n_0 – initial population size; g_{max} – maximum generation;
p_m – mutation rate; m – number of newly generated scores;
$popylation_0$ – randomly generated population of hyperparameter configuration;
while i <= g_{max}
do
    // initialize true fitness values:
    $T_{r_0} = \{(\boldsymbol{\lambda}_i, L_i)\}_{i=1}^{n_0}$;
    // use T_{r_0} to update the Gaussian surrogate model $\hat{L}$:
    $\hat{L}(\lambda) \sim N(\mu(\lambda), \sigma(\lambda))$;
    // where μ – mean, σ – covariance function;
    // apply **selection()** to most promising scores for further mutation:
    $population_{selected} = \mathbf{selection}(population_g)$;
    // apply **mutation()** to the selected scores to breed m new scores:
    $population_m = \mathbf{mutation}(population_{selected})$;
    // calculate true fitness values using $\hat{L}$:
    $T_r = \{(\boldsymbol{\lambda}_i, \hat{L}_i)\}_{i=1}^{m}$;
    // set suboptimal values:
    $\boldsymbol{\lambda}^* = \mathbf{arg\,min}\{\hat{L}_i\}_{i=1}^{m}$;
    // evaluate $L(\boldsymbol{\lambda}^*)$ on training and validation datasets to update true fitness values:
    $T_{r_{g+1}} = \{T_{r_{g+1}} \cup (\boldsymbol{\lambda}^*, L(\boldsymbol{\lambda}^*))\}$;
end
// the suboptimal hyperparameter configuration:
return $\boldsymbol{\lambda}^*_{subopt}$

Fig. 4. The pseudo-code of surrogate-assisted evolutionary strategy for hyperparameter tuning.

According to the algorithm from fig. 4, several initial configuration values of hyperparameters T_{r_0} are randomly generated [16] to preserve the diversity of the initial population. These initial scores are evaluated and used as a training set to construct an initial surrogate model $L(\lambda)$. Next, the algorithm generates a group of new scores, which are assessed in accordance with the surrogate model. Individuals λ^* with better performance and diversity are searched from these newly formed scores based on the acquisition function of the surrogate model. Then, the most perspective ones with true fitness value $(\lambda^*, L(\lambda^*))$ are added to the training set to update the surrogate model. As a result of the algorithm's entire passage on the whole set of hyperparameters, we receive a suboptimal subset of hyperparameters λ^*_{subopt}.

We conducted several computational experiments on the model depicted in fig. 3 based on the evolutional strategy described in fig. 4. The results obtained by our CNN in the classification task are presented in fig. 5.

From the figure above, the training and validation accuracy curves reach 99.1% and 96.1% (fig. 5a) at the last epoch, respectfully demonstrating good convergence on the training and validation datasets; meanwhile, training and validation loss functions gradually decrease and eventually achieve 1.18% and 1.16% (fig. 5b) respectfully. According to fig. 5c, the final AUC score reaches 95.3%. Overall, the obtained results demonstrate that our three-layer CNN can provide complete textural feature extraction for pneumonia and accurately determine the ROI in the limited chest X-ray dataset.

The interpretability of the diagnosis

In this study, we utilized a localization mapping technique called gradient class activation map or grad-CAM [17] as the core of the interpretation module. With localization gradients, it is possible to compute the pixel-wise impact on the last fully connected layer, which in our case is the Dense + Sigmoid layer. In this case, the computational complexity is equal to the whole passage of the network from the first layer to the last one without additional costs.

Let us denote $\varphi_k(x, y)$ the gradient class activation map (grad-CAM) of the *k*-th filter of the last convolution layer at the image's position (x, y). The average pooling operation is performed on this grad-CAM before transferring the image to the last fully connected layer. Let us also assume w_k^c the weight of the last fully connected layer that connects filter k to class c. Therefore, the grad-CAM for class c and at image's position (x, y) is defined as

$$\text{Grad-CAM}_c(x, y) = \sum_{k=1}^{K} w_k^c \cdot \varphi_k(x, y), \quad (2)$$

where K is the total number of images at the output of the averaged pooling layer.

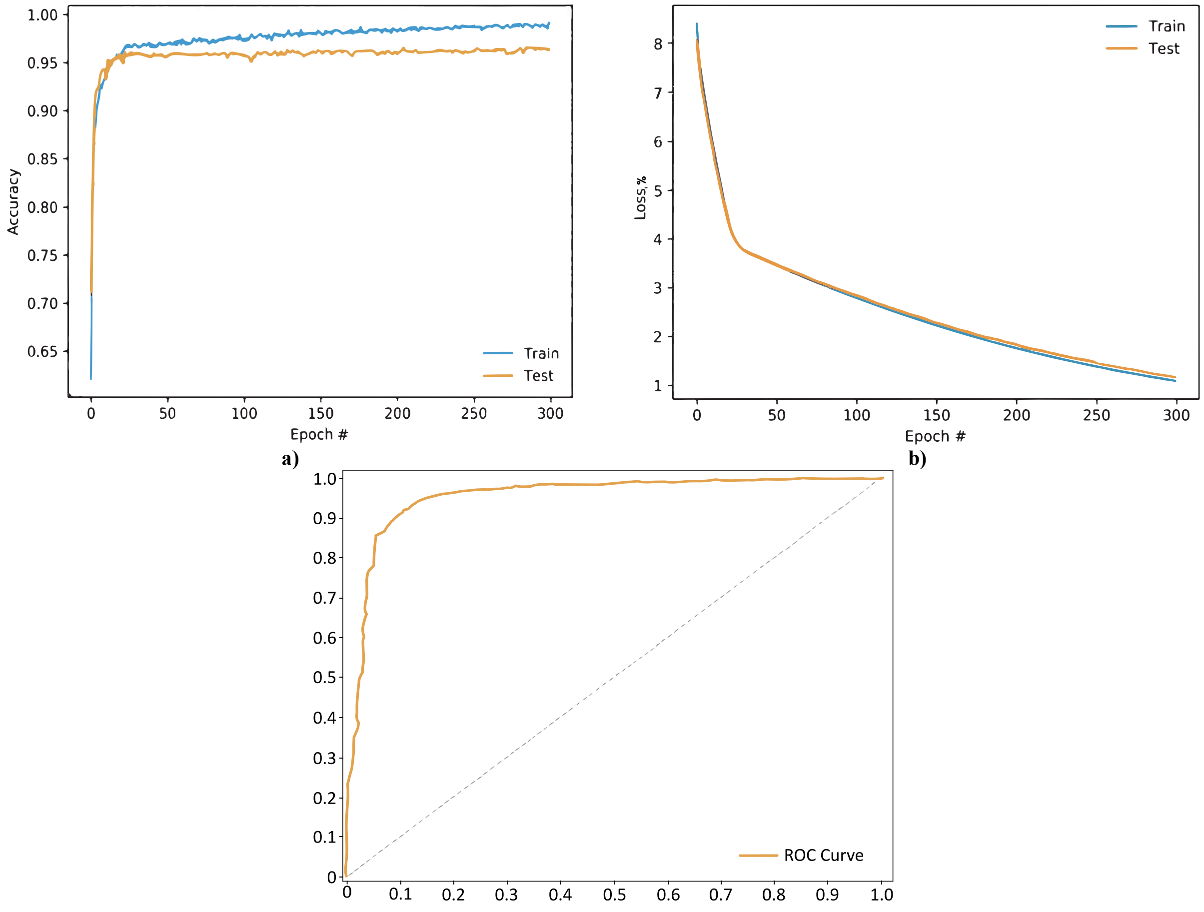


Fig. 5. The classification results obtained by our CNN: a) accuracy curves; b) loss curves; c) the ROC curve is based on true positive (abscissa) and false positive (ordinate) rates.

As a result of applying local gradients, we obtain a set of activation maps after the last convolutional layer with the highest values corresponding to the most substantial influence of class c on the disease prediction. Fig. 6 shows an example of the pneumonia localization using the grad-CAM technique.

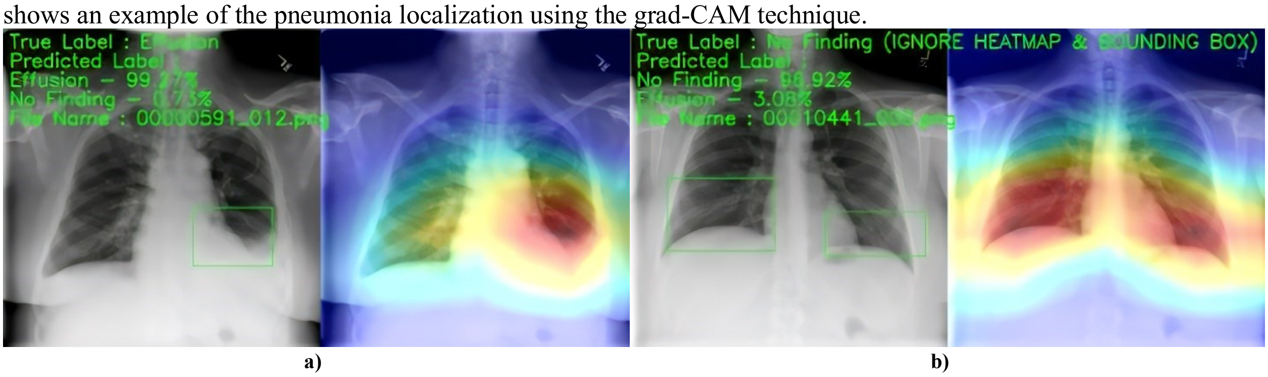


Fig. 6. a) chest X-ray sample with superimposed grad-CAM for pneumonia effusion; b) normal lung condition.

As shown in fig. 6, grad-CAMs allow good localization, as there is only one pooling layer after all convolutional extractors. Note that the superimposed localization maps do not match the size of the original image for easy visualization.

Web implementation

The web-based information system consists of separate modules to provide flexibility and scalability. This approach ensures straightforward modifications to the system in the future. Our system uses ONNX to deploy and transfer models trained either in PyTorch or TensorFlow to web browsers. The system also supports Tensorflow.js to display prediction results obtained by the network in a browser. Overall, fig. 7 shows the dependency graph of all necessary libraries used in our information system.

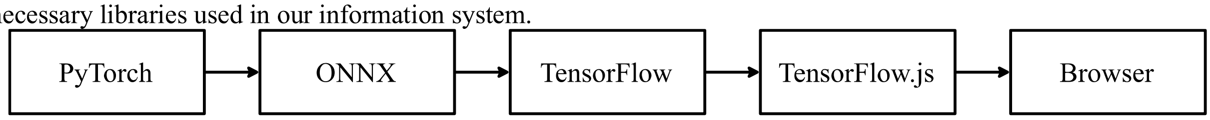
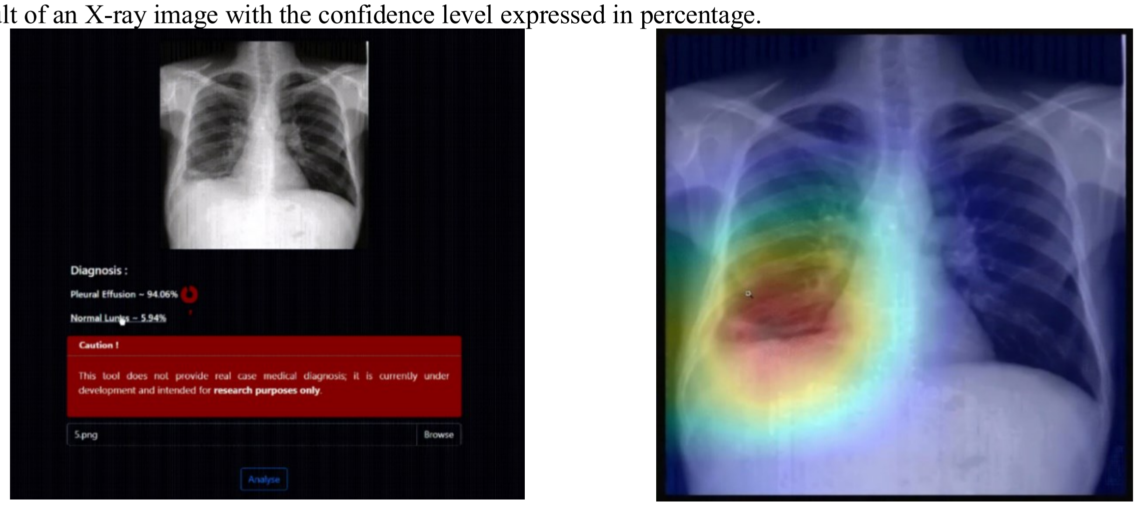


Fig. 7. The pipeline of all necessary libraries used in the information system

The described above toolset packs the model's graph and weights into separate files while deploying a model in a browser. Next, the corresponding script in the browser loads these files, reconstructing the graph and loading the weights to the browser. The script must process the image in the format expected by the model, execute a computational graph, and present the results. Fig. 8 presents the application interface presenting the prediction result of an X-ray image with the confidence level expressed in percentage.



a) b)

Fig. 8. The visual representation of the proposed InfoTech: a) the user interface; b) the results with the superimposed grad-CAM.

In fig. 8, there are the validation results of the system with one image. The model is based on the PyTorch and TensorFlow.js frameworks. The presented InfoTech is available on the GitHub repository by the link: https://github.com/soolstafir/An-Early-Diagnosis-of-Pneumonia-on-Individual-Radiographs.

Conclusions

This study proposes and describes a working prototype of a web-oriented information system for the digital diagnosis of pneumonia on chest X-rays. This system contains three key modules. The first module aims to predict the presence of the disease; for this purpose, we used a classification model based on a convolutional neural network with three convolutional layers and dilated convolution operations. The second module is responsible for setting the hyperparameters of neural network learning based on a modified evolutionary algorithm. The third module is designed to display and interpret the results of diagnosing pneumonia on X-ray images using map activation technology of classes. Combined under one system, these three components form a working tool to assist medical researchers and professional radiologists. It is also worth noting that the web orientation of the system with the local server allows storing personal patient data on the user's computing device, as all calculations are performed locally.

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