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Probabilistic Image Analysis for Chest X-Ray Classification: Integrating Density Functions as Descriptive Features

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Abstract

In this study, we present a technique for chest X-ray image classification by integrating Generalized Extreme Value (GEV) probability density functions (PDFs) with Convolutional Neural Networks (CNNs). The traditional method is related to our proposed method, and the results show significant enhancements in key performance metrics. The proposed method reaches an accuracy of 91.95%, higher than the traditional method's 89.85%, typically enhanced capabilities in accurate classification. Precision is higher in the proposed method at 91.13%, emphasizing its proficiency in correctly identifying positive cases. Specificity is improved in the proposed method (67.22%) compared to the traditional method (61.20%), which represents a lower risk of false positives. The F1-score of 95.01% in the proposed method indicates a consistent balance between precision and recall, underlining its effectiveness in minimizing both false positives and false negatives. These findings suggest that the integration of GEV PDFs and CNNs holds potential for progressing chest X-ray image classification accuracy and reliability, with possible suggestions for improving diagnostic procedures in clinical settings.

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1. Introduction

Medical imaging, typically chest X-ray analysis, aids as a basis in the primary recognition and diagnosis of various pulmonic situations. As the request for precise and automated diagnostic tools continues to rise, there is a serious need for progressive computational methods accomplished of extracting useful features from medical images. In this work, our research presents an approach by integrating probability density functions (PDFs) as extract features in the realm of chest X-ray classification [1]. The base behind integrating PDFs lies in their ability to summarize the statistical distribution of pixel intensities within an image. Unlike traditional feature extraction methods, which are often based on predefined filters methods, PDFs propose a data-driven paradigm that widely characterizes the essential variety of pixel values [2]. This is particularly appropriate in chest X-ray test, where understated nuances in image intensity may hold vital diagnostic information. Chest X-ray datasets expression essential complexities, stemming from varied patient demographics, variations in imaging procedures, and the multifaceted appearances of pulmonary viruses. By implementing PDFs as discriminative features, our study seeks to address these experiments and contribute to the progress of more resilient and flexible diagnostic models. The probabilistic nature of PDFs allows an illustration of image characteristics [3], possibly revealing disease-specific patterns that traditional feature sets overlook. Through this paper, we defined an exploration of the theoretical foundations of probability density functions and their application in the context of chest X-ray image processing. Our methodology covers in conventional approaches, and marking to improve disease classification accuracy and strengthen detection capabilities. Experiential validation on a chest X-ray dataset underlines the efficacy of integrating PDFs as a means to capture and increase informative features. The challenge of diagnosing pneumonia and other lung conditions from chest X-rays remains an important issue in clinical sectors. Conventional imaging methods often suffer from poor accuracy, specificity, and overall reliability, which may lead to misdiagnosis or delayed treatment. These methods often struggle to distinguish subtle differences in X-ray images, leading to false positives and increasing the possibility of missing important cases. The need for more robust and reliable diagnostic tools is becoming increasingly important to ensure accurate diagnosis of lung diseases. To address these shortcomings, this paper proposes the use of enhanced value functions (GEV) combined with (CNNs) to improve the classification accuracy of chest X-ray images, with the aim of improving system research and ultimately reducing the number of inappropriate and negative content.

2. Related Works

E Kotei and R Thirunavukarasu [4], provided a comprehensive review of the state-of-the-art deep learning models used for the automatic detection of tuberculosis (TB) from chest x-ray radiographs, with a focus on Convolutional Neural Networks (CNN) and pre-trained CNN models. They discussed various components of TB detection models, including datasets, data preprocessing, feature extraction, and classification techniques. The review highlighted that pre-trained CNN models generally outperformed CNN models trained from scratch. Additionally, visualization techniques used to interpret "what" and "where" the network is learning are explored, addressing the common criticism that deep learning models are a "black box." The study also outlines the performance evaluation metrics used in the reviewed papers and emphasizes the limitations identified in existing research, offering future directions for improving TB detection using deep learning. The study primarily focused on CNN models and pre-trained CNNs, without exploring more advanced deep learning architectures such as transformers or hybrid models. B Wang, H Pan, A Aboah, and Z Zhang [5], introduced GazeGNN, a novel gaze-guided graph neural network (GNN) designed for real-time disease classification using raw eye-gaze data without requiring the time-consuming preprocessing step of generating Visual Attention Maps (VAMs). GazeGNN integrated eye-gaze data and image information into a unified graph representation, allowing the model to process both image patches and gaze patterns simultaneously. This innovation enabled the development of an end-to-end, real-time disease classification algorithm, making it feasible for integration into radiologists' daily workflows. Experiments conducted on a public chest X-ray dataset demonstrate that GazeGNN outperformed existing methods in classification performance, making it the first work to apply GNNs for the integration of image and gaze data in disease classification. The method not only streamlined the gaze data usage process but also improved accuracy by eliminating the need for preprocessing steps like generating VAMs. While GazeGNN shows promising results in disease classification, the study is limited to public chest X-ray datasets, which may not fully represent the complexities of other medical imaging modalities. J Jeong, K Tian, A Li and S Hartung [6], introduced X-REM (Contrastive X-Ray REport Match), a novel retrieval-based radiology report generation module that improved the accuracy and relevance of automated radiology reports by using an image-text matching score. Unlike previous methods that rely on image captioning or simple retrieval approaches, X-REM leverages a language-image model to better capture the fine-grained interactions between chest X-ray images and corresponding radiology reports. The model's multi-modal encoder utilizes a learned similarity metric for improved retrieval, and outperformed prior methods on both clinical and natural language metrics. Human evaluations indicate that X-REM increases the number of zero-error reports and reduces error severity in comparison to baseline approaches. Although X-REM showed promising results, there remains a gap between AI-generated reports and those written by radiologists, highlighting the limitations of current models in capturing complex clinical nuances. M Maniruzzaman, A Sami, R Hoque, and P Mandal [7], in their study, demonstrated that deep learning models showed significant promise in aiding the diagnosis of pneumonia from chest X-ray images. A study implemented five pre-trained models, including VGG-16, VGG-19, ResNet-50, Inception-V3, and Xception, to detect pediatric pneumonia. Among these models, Xception demonstrated the highest performance, achieving a recall of 97.43%, specificity of 91.02%, accuracy of 95.06%, and AUC of 94.23%. This highlighted the model's superior visualization capabilities and learning ability in distinguishing between normal and pneumonia cases, making it highly supportive for medical professionals. However, the study also acknowledged certain limitations, such as time consumption, inefficiency in multi-label classification, and the need for further optimization. Future work aims to enhance these models by adding layers for multi-label classification and expanding the dataset to improve overall accuracy and efficiency. NW Asnake, AO Salau, and AM Ayalew [8], introduced a deep learning model for pneumonia detection, aiming to improve the accuracy and efficiency of identifying pneumonia from chest X-ray images. The model preprocesses the images, segments them using threshold segmentation, and utilizes the YOLOv3 detector to identify pneumonia cases, followed by classification using Support Vector Machine (SVM) and SoftMax. The results showed impressive performance metrics, with 99% accuracy, precision, recall, and F1-score, indicating high reliability in distinguishing between normal and pneumonia-infected patients. The study also revealed some limitations. While the performance metrics are promising, reliance on SVM and segmentation methods could pose scalability challenges when dealing with larger datasets or more diverse cases. Aseel Muslim Eesa and Mohammad Kaisb [9], focused on image segmentation, and nonparametric kernel functions were applied using a thresholding method. The image was first transformed into grayscale, and the probability density function (PDF) was estimated based on the grayscale data. The highest value of the kernel function was selected as the threshold limit for segmentation. The bandwidth parameter was found to significantly influence the segmentation process, as it affects the accuracy of the PDF estimate, impacting both bias and variance. Proper adjustment of the bandwidth parameter, which depends on sample size, resulted in enhanced segmentation by isolating the most important areas of the image while discarding irrelevant sections. The study also demonstrated that the uniform, Gaussian, cosine, triangular, logistic, and Silverman kernel functions were particularly efficient in extracting key features from the images, providing clear segmentation results by removing unimportant areas. These findings highlighted the effectiveness of kernel functions in image segmentation, emphasizing their potential for feature extraction in medical imaging and other domains. LB Stotts and LC Andrews [10], examined the effect of adaptive optics (AO) configurations, such as tip/tilt ($N = 3$) and full AO ($N = 35$), on the intensity probability density functions (PDFs) in turbulent communication channels. The commonly used log-normal (LN) PDF was found to adequately model the intensity distributions for tip/tilt scenarios but failed to capture the full AO cases, particularly in accurately representing the left-skewness of the PDF. To address this, the study proposed a scintillation index model for full AO, demonstrating that the exponentiated Weibull (EW) PDF better matched the experimental data, including the left-skewness. The results also showed that as AO Zernike modes were added, the PDFs shifted rightward, indicating increased received power, with narrower shape changes. While the LN PDF is suitable for tip/tilt cases, its inability to model full AO configurations makes the EW PDF a more accurate option. However, the study has limitations in fully explaining the performance under varying turbulence levels and should be explored further for broader AO configurations.

3. Chest X-Ray Dataset

A recognition of chest X-ray images leads to accurate clinical diagnoses, mostly when characterized by normal and abnormal cases. In a normal chest X-ray as shown in Figure 1 (left panel), the representation shows clear lungs without any different areas of abnormal opacification. This absence of abnormal opacities is a healthy pulmonary state, helping as a baseline for comparison [11].

Figure 1. Chest X-ray image sample

Bacterial pneumonia in Figure 1 (middle panel), in difference, naturally presents as a focal lobar merging. In the provided case, the consolidation is obvious in the right upper lobe, highlighted by the presence of darker lung tissue (shown by white arrows). This localized merging is a characteristic radiological feature frequently related to bacterial pneumonia, supports clinicians in pinpointing the affected part, and guides to targeted therapeutic interventions [12]. Also, viral pneumonia as shown in

Figure 2 (right panel) manifests with a characteristic "interstitial" pattern that spreads more diffusely over both lungs. Different from bacterial pneumonia, the opacity in viral pneumonia seems in an extra scattered and widespread way, affecting the interstitial places between alveoli. This nuanced radiological variance aids in the variation between bacterial and viral etiologies, contributing to the accurate identification of the causal cause and informing suitable treatment strategies [10]. One of the general pneumonia datasets found on Kaggle is the "Chest X-Ray Images (Pneumonia)" dataset. This dataset is regularly used for pneumonia detection in chest X-ray images. This dataset contains chest X-ray images labeled with binary classes' typical the existence or absence of pneumonia. The images are divided into normal (without pneumonia) and pneumonia classes, providing a good resource for training and evaluating machine learning models for pneumonia detection [11]. Understanding these radiological nuances is key for healthcare specialists in their diagnostic actions.

4. Probability Density Function In Image Analysis

Probability Density Function (PDF) is an important statistical operation that characterizes the probability of a continuous random variable on a specific value [12]. It is a model in probability theory for involving the distribution of values within a dataset. The PDF represents the relative probability of different outcomes, with the area under the curve totaling to one. Essentially, the PDF offers a complete indication of the probability distribution of a continuous variable. It is generally used in numerous fields, including physics, engineering, finance, and data science, to model and examine random phenomena [13]. Probability density functions (PDFs) useful to images provide a strong framework for considering and modeling the distribution of pixel values. By generating histograms and normalizing them, PDFs suggest a brief representation of the probability of changed pixel values found within an image [14]. This statistical approach is involved in numerous image operation tasks, such as segmentation, feature extraction, and texture analysis [15]. Extracted features by using PDFs, can result in important characteristics of the image, aiding in tasks like image improvement, anomaly detection, and classification. Moreover, PDF-based methods can be modified for adaptive processing, to ensure their efficiency in dynamic environments or applications involving developing image data. Applying PDFs to image analysis is considered as powerful the insights increased from the probability distribution to make decisions about the image. Peaks and troughs in the PDF can make segmentation and thresholding in images, improving the capability to separate between different areas or objects. The flexibility of PDF analysis covers its efficacy in machine learning applications, where the distribution of pixel intensities assists as valued input for classification processes. Applying PDFs to images bonds the gap between statistical analysis and image processing, and present a flexible and good toolset for understanding and operating visual data [13]. The Probability Density Function (PDF) for extreme value distributions describes the distribution of the extreme values within a set of random variables. One of the most known methods of extreme value distributions is the Generalized Extreme Value (GEV) distribution, which is frequently applied to model the distribution of the maximum or minimum values from a set of independent and identically distributed random variables. The PDF of the GEV distribution is given by Eq. (1) [14]:

$$f(x;\mu,\sigma,\xi)=\frac{1}{\sigma}\left[1+\xi\left(\frac{x-\mu}{\sigma}\right)^{-\frac{1}{\xi}-1}e^{-\left[1+\xi\left(\frac{x-\mu}{\sigma}\right)\right]}\right]^{-\frac{1}{\xi}} \quad \dots (1)$$

where μ is the location value, σ is the scale value, and ξ is the shape value. The GEV distribution comprises three types of extreme value distributions dependent on the value of ξ as follows:

$\xi>0$:Weibull distribution
$\xi=0$:Gumbel distribution
$\xi<0$:Frechet distribution

Each of these distributions is applied to model various types of extreme values, and the values control the location, scale, and shape of the distribution. The GEV distribution is mainly used in modeling extreme actions in various fields such as hydrology, finance, and environmental education.

5. Proposed Method

Applying extreme value probability density functions (PDFs) as features in an image comprises a targeted examination of the distribution of extreme pixel intensities in an image. Firstly, the PDF for extreme values, such as those found in the Generalized Extreme Value (GEV) distribution, is valued to summarize the probability of extreme intensity occurrences. From GEV, features are extracted to offer valued insights into the extreme characteristics of the image. Statistical measures, such as location, scale, and shape values resulting from the extreme value PDF, suggest a nuanced understanding of the spatial distribution of extreme strengths.

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These extracted features can be essential in improving anomaly detection within the image, as they detention deviations from characteristic intensity patterns. The extreme value PDF-based features can used as segmentation processes, detect regions of interest where anomalies actions are likely to occur. Moreover, these features may be applied to the development of machine learning models, and the distribution of extreme values assists as input for the classification phase. By integrating extreme value PDFs as features in image analysis, this method not only improves the expressive power of statistical modeling but also allows algorithms to discriminate and detect extreme events within the visual data. In GEV equation (1), the x represents the image data, μ represents the mean of the image, and σ represents the standard deviation of the image. The mean (μ) of pixel intensities in an image is calculated using Eq. (2) [15].

$$\mu = \frac{1}{NM \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} x(i,j)} \quad \dots (2)$$

where N and M are the total number of pixels in the image, x(i,j) defines the intensity value of the i,j-th pixel. This formula calculates the mean intensity value across all pixels in the image. It provides a measure of the central tendency of the pixel intensities, representing a typical or average intensity value. In image processing, the mean is often applied to describe the general brightness of an image. A higher mean intensity suggests a brighter image, while a lower average intensity is found in a darker image. The standard deviation (σ) of pixel intensities in an image is calculated using Eq. (3) [15].

$$\sigma = \sqrt{\frac{1}{NM} \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} (x(i,j) - \mu)^{2}} \quad \dots (3)$$

where N, and M are the total number of pixels in the image, x(i,j) defines the intensity value of the i,j-th pixel, and μ is the mean intensity of all pixels in the image. This formula computes the square root of the average squared variances between each pixel intensity and the mean intensity of the image. The standard deviation presents a measure of the amount of variation in pixel intensities. In the domain of image analysis, a higher standard deviation often indicates a greater level of contrast or variability in pixel values, while a lower standard deviation proposes a more unvarying or similar distribution of intensities.

Figure 2(a) shows the samples of the original chest x-ray in both cases (Normal and Pneumonia) and Figure 2(b) shows processed original images by applying the GEV distribution function.

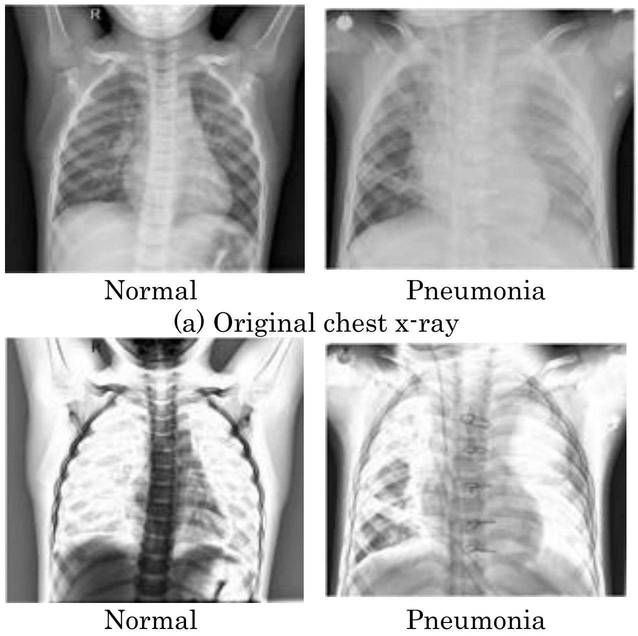

Figure 2. Samples of Chest X-ray of both cases (normal and pneumonia) in (a) conventional and (b) process by GEV

6. The Proposed of CNN Architecture

A. Dataset: There are two datasets prepared for CNN, the first dataset is the original (not processed), and the second dataset is treated with a transformation the original dataset by applying the GEV distribution function. Both datasets contain two subfolders that represent normal and pneumonia classes. The dataset is divided into training and test sets.

B. Architecture: the parameters of CNN proposed are described in Table 1.

Table 1. Architecture of CNN of proposed work.

Input layer	Image 28 × 28 with single channel
Convolution layer	5 by 20
Full connected layer	2
Batch normalization layer	Active
Relu layer	Active
Type	SGDM
Max epoch	4
Validation frequency	20

C. Training: this part needs to set the size of the image, number of image layers, number of classes, and options stated in the above table.

Figure 3 shows the training process of the conventional method, and Figure 4 Shows the training process of the proposed method.

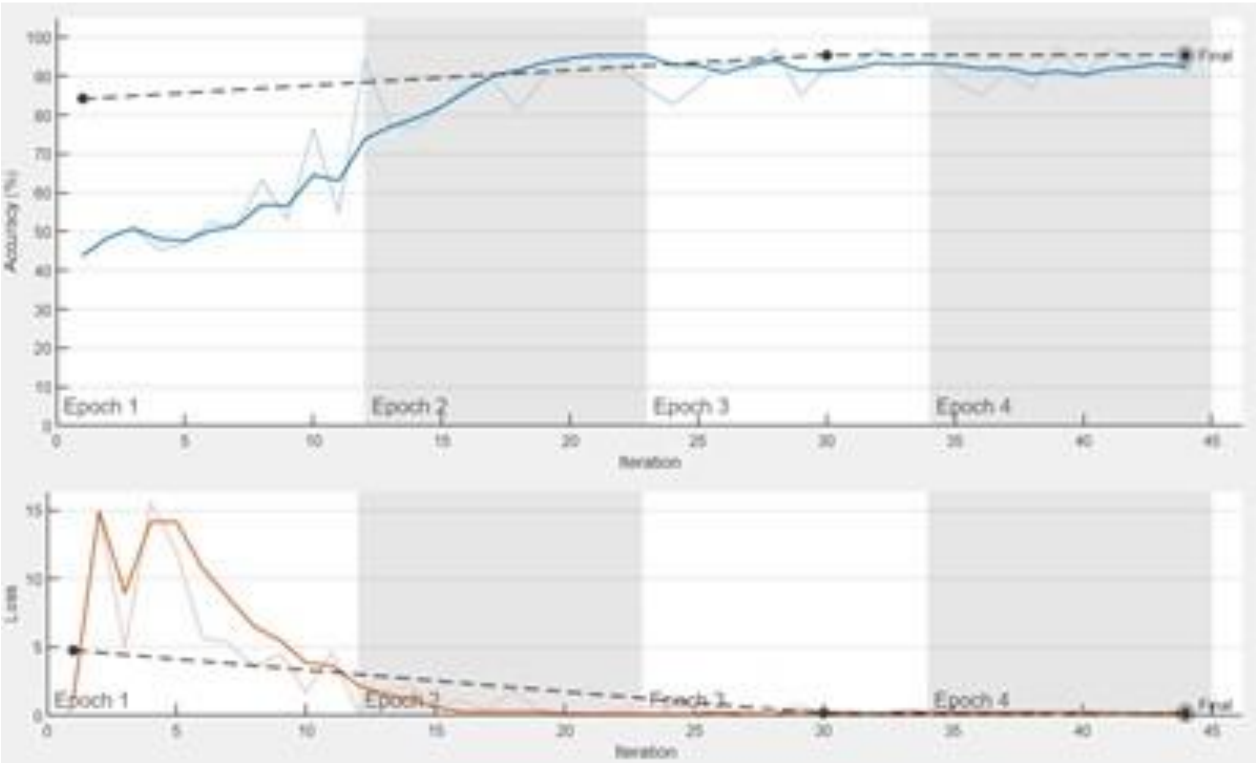

Figure 3. Training Process for Conventional Method

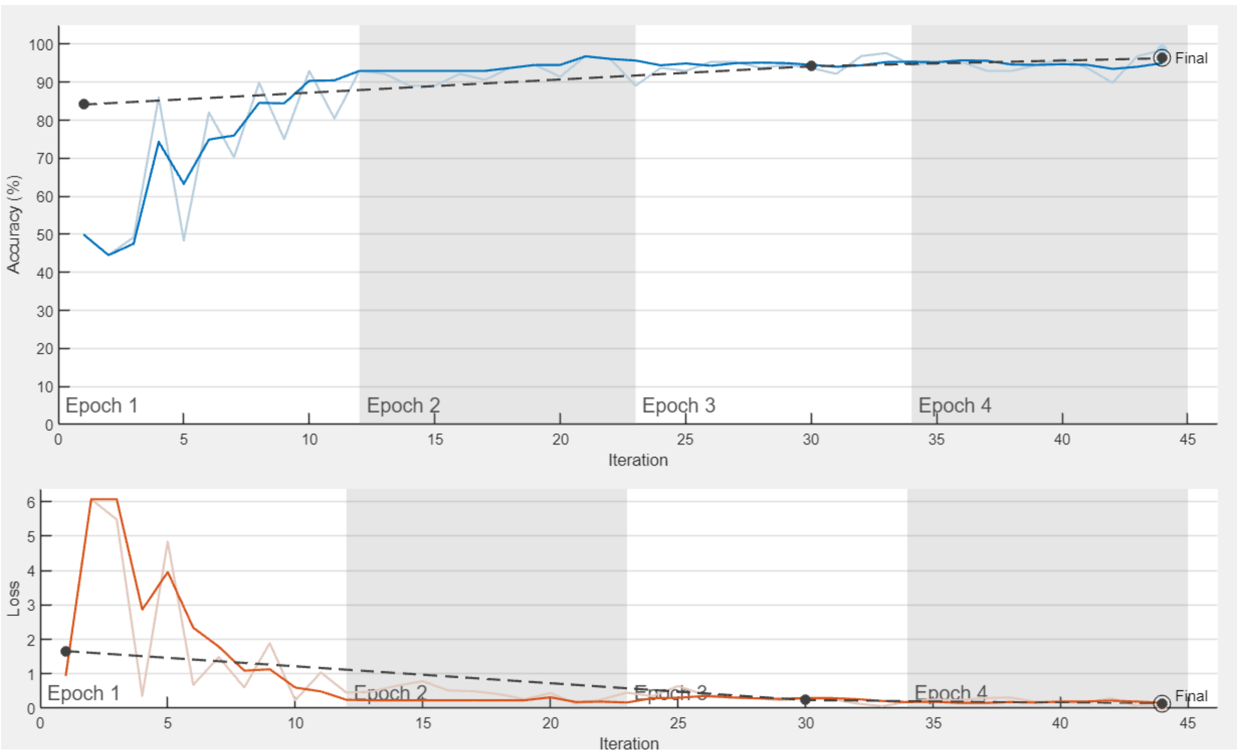

Figure 4. Training Process for Proposed Method

D. Testing: in this stage, evaluate the trained model on a test dataset to assess its generalization to new data. Compute performance metrics such as accuracy, precision, specificity, and F1 score described in Table 2.

Table 2. Evaluation results

Method	Conventional	Proposed Method
Accuracy	89.85%	91.95%
Precision	88.57%	91.13%
Specificity	61.20	67.22
F1-score	93.60	95.01

7. Discussion

In evaluating the X-ray imaging design, the proposed method showed a significant improvement compared to the traditional method. By combining the generalized gene expression likelihood function (GEV) and neural networks (CNNs), the proposed method achieved an accuracy of 91.95%, which exceeded the accuracy of the traditional method of 89.85%. This higher accuracy indicates an increased ability of the GEV-based method to differentiate between normal and malignant cases. The accuracy, which measures the model's ability to identify the correct cases, also improved to 91.13% in the proposed method, compared to 88.57% in the traditional method. This increase in accuracy shows the ability of the proposed method to reduce false positives, an important factor in clinical settings to avoid false positives. The improved accuracy suggests that the proposed method is better at avoiding these incorrect positive classifications. This enhanced precision not only provides more reliable diagnostic results but also helps prevent the negative consequences associated with false positive errors, such as psychological stress and unnecessary medical interventions. The proposed method also shows a great improvement in the specification, which is 67.22% compared to 61.20% of the traditional method. This improvement shows a better ability to reduce false positives. False positives in medical diagnostics, particularly in chest X-ray image segmentation, occur when the model incorrectly identifies normal tissue as being abnormal (malignant or suspicious). This can lead to unnecessary diagnostic tests, patient anxiety, and wasted resources. By improving the model's specificity, the proposed method minimizes these incorrect identifications, thus enhancing clinical decision-making. The F1 score, which balances precision and recall, reached 95.01% in the proposed method, which indicates the accuracy of its performance in reducing both false positives and false positives. Together, these measurements demonstrate the robustness and reliability of the proposed method in processing chest X-ray image segmentation, indicating its potential for future applications in clinical diagnostics.

8. Conclusions

The valuation of results between the traditional and proposed methods for chest X-ray image classification shows improvements in the proposed method. The proposed method, integrating Generalized Extreme Value (GEV) probability density functions (PDFs) and Convolutional Neural Networks (CNNs), validates greater accuracy at 91.95%, superior to the traditional method's accuracy of 89.85%. Also, the proposed method reaches a higher precision of 91.13%, representing its improved capability to correctly identify positive cases. Furthermore, the proposed method shows an improvement in specificity, reaching 67.22%, compared to the traditional method's specificity of 61.20%, signifying a reduced likelihood of false positives. The overall F1-score of 95.01% for the proposed method underscores its well-balanced performance in maximizing true positives and minimizing both false positives and false negatives, emphasizing its potential for proceeding with the accuracy and dependability of chest X-ray classifications. While the results are promising, further research could focus on updating the model and evaluating its performance on different datasets to ensure its usefulness and reliability in real clinical situations.

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