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RESEARCH ARTICLE

Proposal and Definition of an Intelligent Decision-Support System Based on Deep Learning Techniques for the Management of Possible COVID-19 Cases in Patients Attending Emergency Departments

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This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Ethics Committee of Galicia under Protocol No. 2020/271, and performed in line with the Declaration of Helsinki.

ABSTRACT The COVID-19 pandemic drastically transformed the integration of technology into medicine, testing the ability of health systems to make quick and effective decisions. This has been especially noticeable in emergency departments, which were overwhelmed by the massive influx of patients. In this context, this article presents the design, development, and proof of concept of a new intelligent decision support system applied to the management of patients suspected of having COVID-19 upon their arrival at an emergency department. To achieve this, starting from our proprietary database of chest X-rays (CXRs) collected at the Ribera Povisa Hospital, two modules based on the use of convolutional neural networks (CNNs) were sequentially run. The first was based on the DenseNet-121 model to identify whether a pneumonia condition was presented in the CXR, while the second was based on the COVID-Net CXR-S model and aimed to quantify the severity of airspace opacity in the CXR on a scale 0–24. Thus, based on this architecture, it will be possible to make predictions based on the CXR of new patients that, after interpretation, might allow physicians to determine whether cases are high-risk and, for example, should be admitted to the intensive care unit. Although the results we obtained were encouraging, it is important to note that this proposal is still

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at a conceptual stage of development and so future work will be required to validate it in real environments and develop techniques that can help explain its results.

INDEX TERMS Artificial intelligence, convolutional neural networks, decision making, deep learning, decision support systems.

I. INTRODUCTION

The COVID-19 pandemic posed a considerable challenge to healthcare systems [1], [2], [3], [4]. These situations highlighted the need to seek a balance between efficient resource management and safe decision making, even in the initial stages of disease when the tools and knowledge required to achieve this were not available. In particular, it is relevant to highlight the pressure experienced by the emergency services [5], which were overloaded on numerous occasions because of the high number of patients, shortage of beds, and especially by the lack of agile decision-making processes. All the above highlights the need to design specific tools that allow patients with more severe disease to be identified, thereby facilitating decisions regarding hospitalisation and even admission to the intensive care unit (ICU). In this context, thoracic imaging techniques are already widely used in emergency departments to evaluate the possible severity of COVID-19-associated pneumonia [6], [7], [8]. However, quantification of disease extent is subject to interobserver variation, nonspecific interpretation, and understudied correlations with clinical outcomes. In addition, many radiologists find it difficult to diagnose the presence of coronavirus because it is difficult to differentiate between pneumonia caused by COVID-19 and other types of illnesses.

Generally speaking, various tools and mechanisms have been developed in the health field in recent years aimed at facilitating and streamlining arduous decision-making processes [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22]. These tools are commonly known as decision support systems (DSS), and it is now increasingly common for them to integrate techniques from the field of artificial intelligence (AI). Several unique proposals have already been presented specifically regarding COVID-19, many of them focused on image analysis. In this sense, the development of AI techniques focused on image processing is increasingly common and promising and can be of great help in the field of radiology [23], [24], [25], [26].

Focusing expressly on COVID-19, it is worth highlighting various proposals supported by the use of deep learning (DL) techniques [27], [28], especially convolutional neural networks (CNNs), which are very useful for image analysis. For example, Narin et al. [29] used five models based on pre-trained CNNs, including ResNet50, which demonstrated outstanding performance with an accuracy of 96.1% in classifying COVID-19 using X-ray images. Similarly, Sahinbas and Catak [30] experimented with five different pretrained models, including VGG16, VGG19, ResNet, DenseNet, and InceptionV3 on a balanced set of 140 X-ray images (70 positive and 70 negative for COVID-19), and achieved an accuracy of 80% with the VGG16 model. Along these same lines, Medhi et al. [31] reported 93% accuracy in detecting COVID-19 using a CNN and a dataset with 150 X-ray images. Likewise, Ozturk et al. [32] presented a study to distinguish between patients with and without COVID-19, reaching an average accuracy of 98.08% for the detection of the disease and with average sensitivity, specificity, and F1 score values of 95.13%, 95.30%, and 96.51%, respectively, using DL neural networks and X-ray images. Similarly, Babukarthik et al. [33] proposed a model based on Genetic Deep Learning Convolutional Neural Networks (GDCNN) to detect COVID-19, which they built from a set of 5,000 X-ray images obtained from a public repository; these authors achieved an accuracy of 97.23%, with sensitivities and specificities of 98.62% and 97%, respectively.

In contrast, other specific AI models should also be considered for the generation of severity scores, such as those presented by Li et al. [34] and Zhu et al. [35], which showed an excellent correlation between AI and expert results, reaffirming the feasibility of use and accuracy of AI models in the assessment and monitoring of lung disease severity in COVID-19 cases. These studies not only underline the wide range of current approaches and depth of research in this field, but also highlight the enormous potential and challenges presented by the use of DL and CNN in the classification, quantification, and prediction of disease severity based on lung involvement in COVID-19 cases, in so providing valuable tools to support decision-making in healthcare fields.

This current work presents the design, development, and proof of concept of a new intelligent decision support system for application in the management of patients suspected of having COVID-19 who attend emergency services. Thus, once a patient has tested positive for COVID-19 and has received chest X-ray (CXR) results, two modules based on DL techniques and focused on the classification of CXRs are deployed. The first one tries to determine if the patient has pneumonia. If this is the case, the second one seeks to determine the associated disease severity by calculating an index score ranging from 0 to 24 points. The deployment of this system is expected to speed up the detection of patient cases that require greater attention, thereby allowing the necessary measures to be taken quickly and efficiently.

The present article is organised into five sections. Section II addresses the presentation of the database we employed in this work, presenting the conceptual description of the intelligent system and its implementation through a software artefact. After that, section III presents a case of practical application to exemplify the operation of the system as a proof of concept. In section IV, we discuss the results we obtained

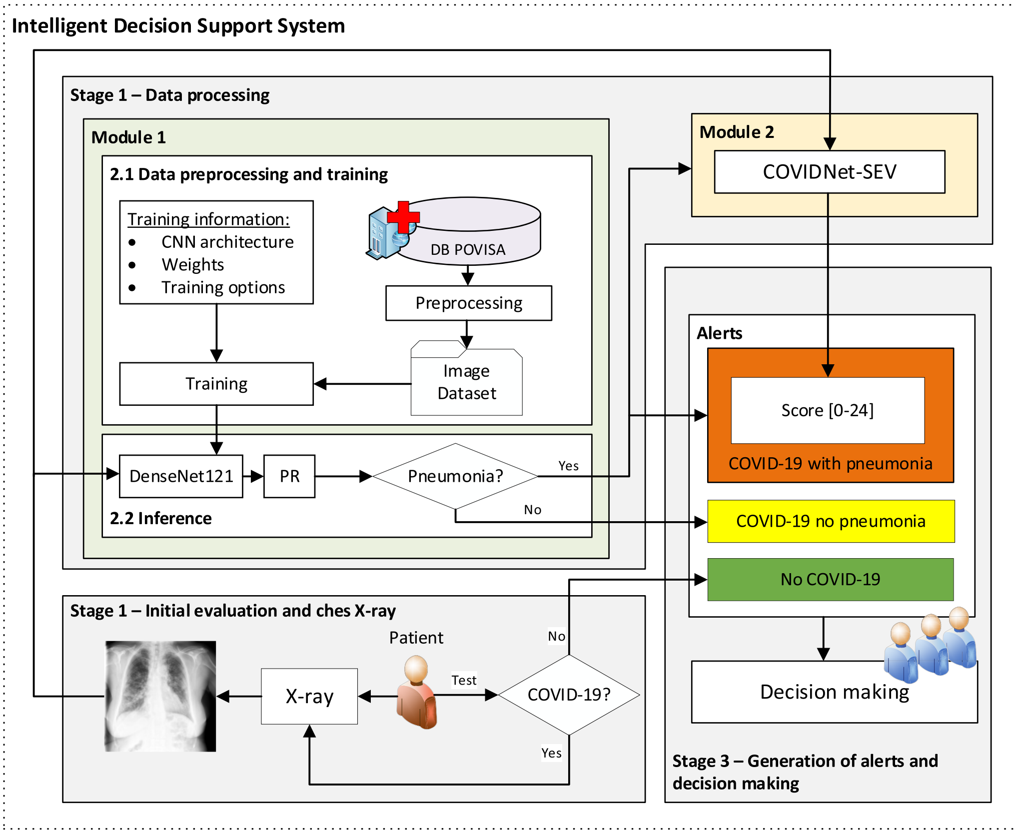

FIGURE 1. Flow chart of the intelligent decision support system.

and finally, section V describes the conclusions obtained and recommended future lines of work.

II. MATERIALS AND METHODS

A. DESCRIPTION OF THE DATABASE

The database used in this study came from the Pulmonology Department of the Ribera Povisa Hospital (Vigo, Galicia, Spain). The study was conducted in accordance with the Declaration of Helsinki and approved by the Ethics Committee of Galicia (protocol code 2020/271). The data it contains were collected between March 2020 and February 2021 and include CXRs labelled by two thoracic radiologists with more than 10 years of experience each. The data collection process should be understood as a continuous series of cases in which patients were recruited as they attended the emergency department at our hospital, thereby making our sample representative of the general population. These images belong to patients who had a positive PCR (polymerase chain reaction) test result for COVID-19 upon arrival at the emergency department. Both posteroanterior (PA) and anteroposterior (AP) views were included in this work. Once a CXR is produced, it is saved in Digital Imaging and Communication In Medicine (DICOM®) format and is managed by the Picture Archiving and Communication System (PACS) at the hospital, from where the images were extracted. In our case, the IMPAX PACS was used (version 6.6.1.4024, 2016, Agfa HealthCare N.V., Belgium). The database contained 2,438 images, of which 1,450 were associated with the pneumonia label (59.5%) and 988 with the non-pneumonia label (40.5%). Of these, 533 images were reserved to carry out tests with the first module of the system.

In addition, from the complete collection of images, 200 were randomly selected for analysis with the second system module, which focused on assessing the airspace opacity severity (ASOS). Quantification of ASOS is tedious and impractical given the volume and complexity of the work carried out in the daily practice of radiologists, but nonetheless provides valuable information to evaluate progression and risk stratification. In this case, two expert thoracic radiologists independently assigned each image a severity score based on their visual estimation of the percentage of lung affected by airspace opacity. To structure this evaluation, each lung was divided into six quadrants. The quadrants were scored as follows: 0 for the absence of lesions, 1 for 0–25% involvement, 2 for 25–50%, 3 for 50–75%, and 4 for more than 75% involvement. Thus, the total possible score ranged from 0 to 24 [36], [37]. To consolidate a definitive numerical label for each image, the average of the scores given by the experts was calculated and rounded to the nearest integer.

B. CONCEPTUAL DESIGN OF THE SYSTEM

The flow chart in Fig. 1 presents the different stages of the intelligent system proposed in this work.

Stage 1 (Initial evaluation and chest X-rays): The first stage of the proposed system focuses on the initial patient evaluation. Upon arrival at the emergency department, a COVID-19 test is performed and in positive cases, a CXR is then performed, as indicated in Fig. 1.

Stage 2 (Data processing): After the initial evaluation, if the patient had COVID-19, the CXR is processed by the intelligent system. To do this, two modules based on the use of CNNs are ran sequentially. Prior to the CXR analysis, the images were pretreated by cropping them to omit any areas not belonging to the CXR. This process was carried out with the entire database prior to the training process. In the case of the first module, once the CNN has been trained, it is then possible to analyse the CXR of a new patient. This module output a metric with a value between 0 and 100, referred to as the Pneumonia Risk (PR). After interpreting this value, it is possible to discriminate between patients with and without pneumonia.

If the patient presents pneumonia, we move on to the second system module, which attempts to determine the severity of the pneumonia by quantifying the ASOS. To achieve this, a new CNN called the COVID-Net CXR-S is deployed [38]. Based on the CXR of the new patient, this process produces a value varying between 0 and 24 according to the associated disease severity detected. In turn, it is important to note that in the future, once the system is validated and enters the production phase, and as new images are collected, it will be advisable to periodically reassess its predictive capacity, scheduling subsequent time to retrain the CNNs.

Stage 3 (Generation of alerts and decision making): When faced with a new patient, and if they presented COVID-19, a system output label of pneumonia or non-pneumonia is obtained along with the severity indicator of airspace opacity. Based on this classification, the system implements a series of alerts following the rules established for patient management:

- In cases where pneumonia is not detected, no additional actions are required.
- If the patient presents pneumonia and $0 < \text{ASOS} < 5$, monitoring is recommended.
- If the patient presents pneumonia and $5 < \text{ASOS} < 15$, hospitalisation is recommended.
- If the patient presents pneumonia and $15 < \text{ASOS} < 24$, then they should be admitted to the hospital ICU.

These guidelines allow medical staff to efficiently identify patients requiring priority care, thus optimising the decision-making process. It is crucial to note that these rules are also subject to review and adjustment based on new evidence and clinical practices, allowing thresholds and recommendations to be adapted, as necessary.

C. SYSTEM IMPLEMENTATION

This section addresses the implementation of the system described in section *B. Conceptual design of the system.* Python (Version 3.7.10) along with the TensorFlow 2.4 library was used to train and test the models. In addition, MATLAB® (version R2023b, Natick, MA, USA) was used together with the App Designer Toolbox [39] to develop a graphical interface that facilitated interaction with the developed models. The model calculations were conducted in the cloud on a machine with 8 virtual CPUs (30 GB RAM) and a NVIDIA T4 GPU. Figure 2 shows a screenshot of the interface we developed that shows three boxes, with each one relating to the stages previously described in section *B. Conceptual design of the system.*

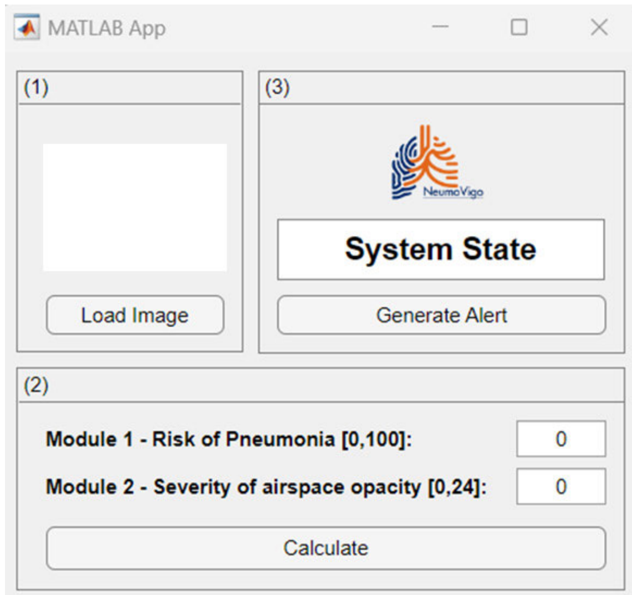

FIGURE 2. Screenshot of the application developed in this work. In panel (1), the CXR to be analysed is selected. In panel (2), the image is processed by the system to determine the risk of pneumonia and, if applicable, the severity of the opacity of the airspace. Finally, panel (3) generates alerts and addresses the associated decision making recommendations.

1) INITIAL EVALUATION AND CHEST X-RAYS

The CXR associated with each patient had to be entered into the application through the panel shown in Fig. 2. It is important that the images of new patients are obtained under conditions similar to those used in the construction of the system in order to maximise its precision.

2) DATA PROCESSING

Once the CXR images from the patient have been uploaded, their treatment is then passed through the system. This treatment is addressed through two modules that run sequentially. The first one deploys a CNN for classification designed to determine whether the patient has pneumonia. While the second deploys a regression CNN that tries to estimate ASOS.

a: MODULE ONE—DIAGNOSTIC

To define the inference engine of the first module, we started with the set of images mentioned in section *A. Description of the database*. Prior to training the model, all the images were rescaled to satisfy the requirements of the CNN

TABLE 1. Training hyparameters for convolutional neural networks.

Parameter	Value	Comment
Optimiser	Adamax	This is a variant of Adam based on the infinity norm.
Epochs	20	-
Learning rate	0.0005	-
Loss	Categorical cross entropy	-

input layer to be used (224 × 224 × 1). It is important to clarify that the starting images were square, so they were not deformed with scaling. Of the total set of images, 533 (approximately 20% of the starting images) were randomly reserved for testing. Of these, 317 of the patients had pneumonia (59.5%). The remaining images were used in the CNN training process. Of the total number of images in the training set, 15% were reserved for validation in order to facilitate hyperparameter tuning.

To give an example of the operation of the system, we started from the Densenet-121 architecture [40] that had previously been trained on the ImageNet data set and adapted its output for two classes (pneumonia versus non-pneumonia). The use of a pre-trained network (an approach known as transfer learning) had significant advantages such as reduced training time and smaller data set requirements, given that the network already contained initialised and non-random weighting. Although Densenet-121 was chosen in this case, other CNN architectures could be chosen, as long as they provide satisfactory results. Hyperparameter optimisation was performed by conducting preliminary tests to select the best hyperparameters for this specific model. These tests involved experimenting with different learning rates, optimisers, and the number of epochs to identify the combination that yielded the best performance on the validation set. These hyperparameters are summarised in Table 1.

After training the model, the PR score is output from the network when it is supplied with new CXRs. This indicator aims to represent the risk of a patient developing pneumonia. Although its true value is between 0 and 1, to facilitate its interpretation it is scaled between 0 and 100. However, a threshold value must be established based on the PR in order to decide if a patient has this condition. To determine this value, we undertook a graphical optimisation similar to that described by Casal-Guisande et al. [11], selecting the threshold value that maximises the Matthews correlation coefficient (Mcc) [41], [42], [43] associated with the test set. The Mcc equation is presented in equation (1); the abbreviations used in the equation are as follows: TN = true negatives, FN = false negatives, TP = true positives, and FP = false positives.

$$\mathrm{Mcc} = \frac{\mathrm{TN} \cdot \mathrm{TP\text{-}FN} \cdot \mathrm{FP}}{\sqrt{(\mathrm{TP{+}FP}) \cdot (\mathrm{TP{+}FN}) \cdot (\mathrm{TN{+}FP}) \cdot (\mathrm{TN{+}FN})}} \tag{1}$$

We chose to use Mcc over other possible metrics such as the precision metric because of its ability to behave appropriately even with unbalanced data sets. In this case, the test set we used presented a slight imbalance, with 59.5% of the patients presenting pneumonia and 40.5% without a pneumonia diagnosis. Fig. 3 shows the different Mcc values for the different threshold values. The optimal Mcc (0.67) is presented for a threshold value of 11.

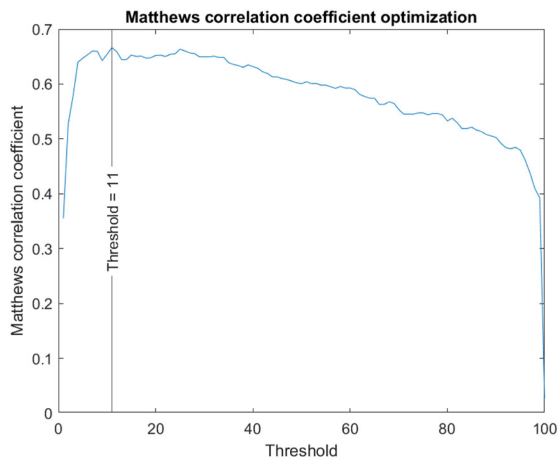

FIGURE 3. Determination of the optimal threshold based on the value of Mcc.

Next, the associated receiver operating characteristic (ROC) curve and system operating point, which is related to the aforementioned optimal threshold, were calculated for the test set (Fig. 4). In this case, the Mcc was 0.67 and at this point the sensitivity and specificity were 0.90 and 0.76, respectively.

b: MODULE TWO—PROGNOSTIC

As previously mentioned, if the patient is diagnosed with pneumonia by the first system module, they are then moved on to the second module which attempts to quantify the ASOS. Given the small number of CXRs available (200), in this case we decided to integrate an already trained model, the COVID-Net CXR-S, into module two. The latter is a CNN developed by Wang et al. [38], [44], to predict ASOS in patients that tested positive for COVID-19 based on a

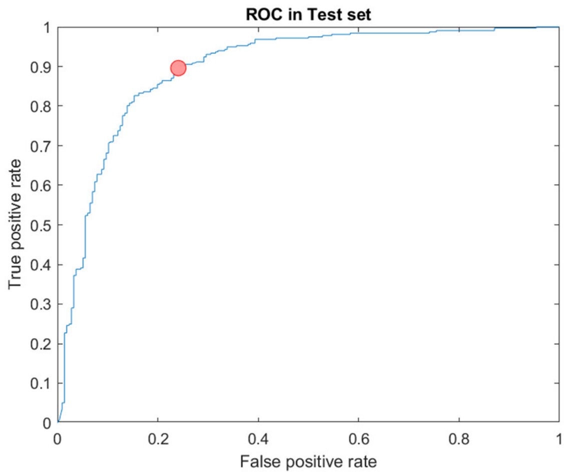

FIGURE 4. The receiver operating characteristic curve for the test set with the optimal operating point highlighted.

CXR image, which is available for public use in a GitHub repository [45]. For their training and implementation, the authors used Keras with the following hyperparameters [44]: learning rate = 0.0002, number of epochs = 22 and batch size = 64. In this present case, the images had to be rescaled to 480 × 480 × 1 to match the dimensions of the COVID-Net CXR-S input layer.

The RMSE (root mean square error), the square root of the sum of the square of the residuals between the real value and the value predicted by the model, is often used to quantify the precision of regression models. The equation to calculate RMSE is shown in equation (2) and ideally, the lower this value, the better the fit.

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{m}} \sum\nolimits_{\mathrm{i}=1}^{\mathrm{m}} (\text{Real value}_{\mathrm{i}} - \text{Predicted value}_{\mathrm{i}})^2} \tag{2}$$

A RMSE of 6.14 was obtained in the tests carried out with COVID-Net CXR-S using our set of 200 patients. Thus, given that the variable to be predicted varies between 0 and 24, we understood that there was a moderate level of error in relation to the total range of the variable. Nonetheless, in the future it would be advisable to fine-tune this already trained model if a larger database is available.

3) ALERT GENERATION AND DECISION MAKING

After analysis of the CXR, the PR and ASOS scores are obtained and the associated alerts are generated based on their interpretation, as shown in Fig. 2, panel 3.

III. CASE STUDY

This section presents a practical application case to provide an example of how the system operates. This is essentially a proof of concept and in no case is intended to validate the tool or compare it with other existing state-of-the-art tools. The system must be validated through its intensive and controlled use in real environments, where it will be possible to analyse its clinical usefulness. However, it is important to note that the data used in this example was from a test set independent of the system training and validation sets.

A. INITIAL EVALUATION AND CHEST X-RAYS

From among the patients available in the test set, a patient with pneumonia was selected at random. Data from this patient was not used in the process of constructing the system. The patient was a 65-year-old woman and the CXR from this case is shown in Fig. 5.

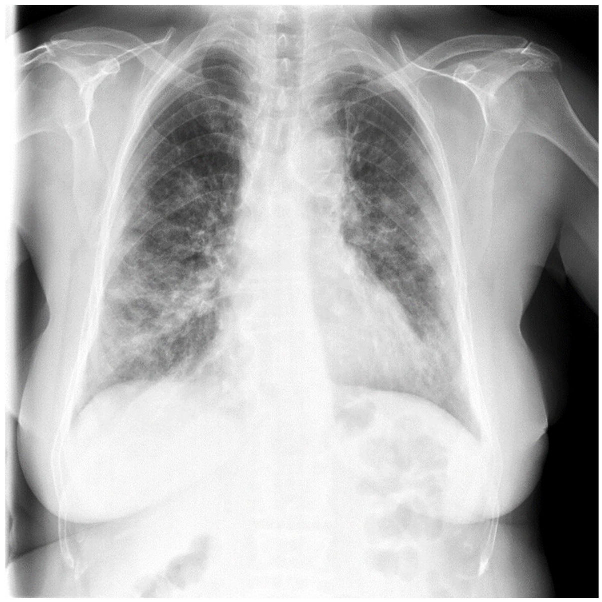

FIGURE 5. The chest X-ray of the example patient under study.

The patient had been evaluated upon arrival at the emergency department and had tested positive for COVID-19; her CXR was classified as positive for pneumonia. In turn, after independently evaluating the CXR, two thoracic radiologists rated the ASOS at 9 points.

B. DATA PROCESSING

Once the patient image was loaded into the system, its analysis was undertaken by clicking the ‘calculate’ button in panel 2 of the application. Next, the PR and ASOS were obtained, producing values of 100 and 9.93, respectively, as shown in Fig. 6.

C. ALERT GENERATION AND DECISION MAKING

Analysis of the image identified a PR exceeding the preset threshold, thereby generating the Pneumonia label. Subsequent analysis by the second module revealed that the patient had an ASOS rated at approximately 10 points. According to the predefined rules for the classification and management of patients based on the ASOS in the context of this system, this specific patient case fell within the range that advises hospitalisation ($5 < \mathrm{ASOS} < 15$). Therefore, hospital admission was proposed by the system with the aim of

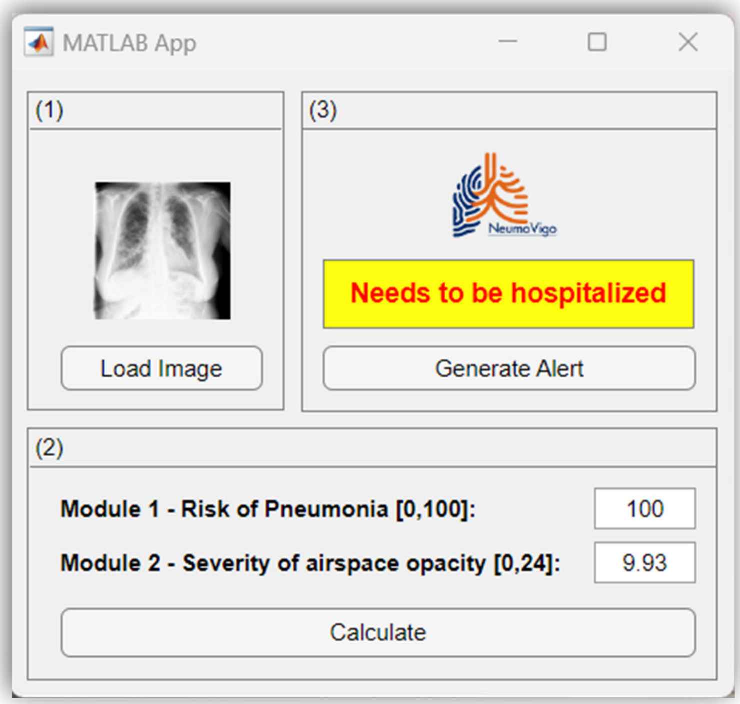

FIGURE 6. Screenshot of the case study.

providing the patient with adequate treatment and to closely monitor her health status. In this case, these predictions were consistent with the actual clinical labels for the patient and its recommendation also aligned with the clinical practices suggested by the attending clinicians.

IV. DISCUSSION

This article introduces the design, development, and proof of concept of a new intelligent decision support system supported by DL techniques applied to the interpretation of CXRs, with the aim of improving the management of patients with COVID-19 who come to the emergency services. The system we present here responds directly to the growing demands on healthcare services that have arisen from the COVID-19 pandemic while also helping to prepare us for potential future pandemic scenarios. By incorporating advanced DL technologies for image analysis, the proposed system not only optimises the accuracy and agility of the diagnosis of pneumonia, but also provides an assessment of the severity of patient conditions. This information is very important for efficient treatment and resource allocation, especially under conditions of high demand such as those experienced at the height of the recent pandemic. It is important to clarify that the associated severity of a given diagnosis should not only be considered when the patient arrives at the emergency department but should also facilitate their follow-up and monitoring. This would allow continuous optimisation of resources and prioritisation of more complex and costly interventions.

Likewise, and unlike conventional methods that predominantly rely on the visual interpretation and judgment of radiologists, the proposed system introduces a quantitative and uniform methodology for the analysis of radiographs. In this sense, it is also worth highlighting the shortage of expert radiologists available to interpret CXRs [46], a problem that further intensified during the COVID-19 pandemic. This deficit is such that, in some centres, these images are diagnosed by personnel less qualified than radiologists expert in CXRs [47]. Thus, by automating the diagnosis and quantification of severity, the system presented here not only minimises interobserver discrepancies, but also alleviates the burden on health professionals who would then only have to validate the proposal made by the system, therefore streamlining their clinical practice. Therefore, once this system advances to later stages of development and is validated in real environments, it could be integrated into routine clinical practice to support radiologists in the diagnosis of patients with COVID-19 pneumonia. Thus, it would improve and simplify this task, especially for radiologists with less experience working with chest images. In addition, although the pandemic associated with COVID-19 seems to be subsiding and no new waves are expected, we believe that this proposed system could be used in pneumonias of other aetiologies with similar radiological presentations.

The system we designed was structured around two CNNs that work sequentially: the first seeks to identify pneumonia in a CXR image and the second, if applicable, quantifies the ASOS. Module one leverages the advantages of transfer learning techniques by employing the Densenet-121 network, previously pretrained with the ImageNet dataset. The decision to use DenseNet-121 was based on careful consideration of its outstanding performance in previous work reported in the academic literature. For example, Kamal et al. compared eight pre-trained models on two different data sets and found that, with an accuracy of 98.69%, DenseNet-121 outperformed the others, with these authors also highlighting its ability in accurately classify COVID-19 in X-ray images [48]. Similarly, Kassania et al. [49] evaluated DL-based feature extraction methods and recognised DenseNet121 as the most effective, achieving an accuracy of 99%. Furthermore, in binary and multiclass classification contexts, Hira et al. observed that DenseNet-121 achieved accuracies of 99.32% and 97.55%, respectively, outperforming other well-known CNN architectures [50].

Of note, transfer learning effectively solves one of the main challenges of DL: the lack of large, labelled data sets. Hence, by using this pre-trained model, our system benefited from prior learning and we were able to adapt it to detect specific patterns of COVID-19 pneumonia. This resulted in a robust and reliable model, with area under the curve (AUC) values exceeding 0.9, thus ensuring accurate diagnoses even with a reduced number of images.

As for the second module, the integration of COVID-Net CXR-S [38], a model already validated by the scientific community, also provided reliable results, as confirmed when its use with our database resulted in a RMSE close to 6. Furthermore, the synergy of both models was particularly beneficial: the system not only distinguished between the presence and absence of pneumonia, but also provided an estimate of the disease severity based on ASOS. This approach would significantly enrich the clinical decision-making process, providing a more complete and nuanced view of the condition of each patient.

The quality and uniformity of the database used are crucial for the development of coherent and effective DL models. Most state-of-the-art work has employed databases available on the internet, thereby mixing patient cases collected under different conditions. This aspect represents one of the outstanding strengths of this present study: we used our own exceptionally curated database, compiled by us at the Ribera Povisa Hospital. The images we included were collected using the same radiography equipment, were labelled following a standardised protocol, and was reviewed by two expert radiologists to ensure accuracy and consistency.

The proof of concept results we obtained underline the effectiveness of the system to differentiate between patients with and without pneumonia and to accurately quantify disease severity, consistently aligning with evaluations performed by expert radiologists. The high agreement between system-generated scores and expert assessments not only confirmed the validity of the approach, but also highlighted the potential ability of the model to function as a reliable tool in clinical settings. In any case, once the system advances to later stages of development, intensive clinical validation in real-world settings will be required prior to its clinical use.

Implementing advanced metrics such as the Mcc to optimise the pneumonia detection threshold further enhanced the accuracy and reliability of the system. In particular, the use of the Mcc provides a robust measure of model performance with imbalanced data sets, ensuring that the system maintains a high level of accuracy in identifying pneumonia cases, even when the distribution of classes is not uniform. In this context, the Mcc value of 0.67 we obtained for module one highlights the remarkable predictive ability of the system, underlining its effectiveness even in challenging diagnostic scenarios.

Therefore, in our opinion, the proposed system has considerable potential to optimise the response capacity of health systems when facing the COVID-19 pandemic or other similar situations. Thus, offering this tool as an effective means for rapid and accurate diagnosis positions it as a valuable resource in the clinical management of COVID-19. Given the innovative nature of this technology and the constant advances in the field of DL, it would be interesting to expand and enrich our database with new cases, which would not only improve the robustness and capacity of the model for generalisation but would also allow a broader range of clinical manifestations of the disease to be captured. Furthermore, exploring new CNN architectures in this context may reveal more efficient and accurate approaches to medical image processing and analysis.

A. LIMITATIONS

Despite the promising results we have obtained in this study, there are several limitations to this work that should be acknowledged:

- Conceptual development phase: Our system is in the concept development stage at the moment and this work is an important benchmark where we showed the utility of the system with a proof of concept. However, COVID-19 is currently under control and it does not seem foreseeable that new waves like those experienced in the past will occur again which, to some extent, will make it difficult to validate this model in real situations in which the radiology service is put under such high levels of demand.
- It should be mentioned that our study was carried out using the data from the Ribera Povisa Hospital (Vigo, Galicia, Spain), and one of the strengths of our study may also be one of its limitations – the size, variability and quality of the database. The sample may not be representative of the variability associated with COVID-19 in different populations because only one hospital database was used. In addition, although we tried to minimise inter-observer variability by having two expert radiologists perform the assessments, there was a degree of dependence on visual interpretation of the images, which could have introduced some variability and error in the definition of the labels.

TABLE 2. Benchmarking.

	Diagnosis	Prognosis	Diagnosis and prognosis
Narin et al. [29]	x	-	-
Sahinbas and Catak [30]	x	-	-
Medhi et al. [31]	x	-	-
Ozturk et al. [32]	x	-	-
Babukarthik et al. [33]	x	-	-
Li et al. [34]	-	x	-
Zhu et al. [35]	-	x	-
Chamberlin et al [51]	-	-	x
Our proposal	-	-	x

- Transfer learning and black box models: In module 1 (diagnosis), a pre-trained CNN adapted for prediction with radiographs was used. Although transfer learning strategies were very useful for reducing training times and the volume of data required, they can also limit the versatility of the model. Furthermore, although CNNs are very effective for image analysis tasks, they are black box models that lack explainability. Thus, this lack of transparency may limit confidence and adoption by healthcare professionals.

B. BENCHMARKING

To facilitate understanding of the usefulness and relevance of our proposal, a detailed comparison with existing state-of-the-art work is presented in Table 2. This comparison considers three criteria, the first focusing on systems that focus exclusively on diagnosis, the second on those that focus solely on prognosis, and the third on those that simultaneously focus on both aspects (diagnosis and prognosis).

In general, most of the work previously published in the academic literature and shown in Table 2 focused on one of these two areas (diagnosis or prognosis) but did not integrate them both. This serves to highlight the novelty of the tool proposed in this current work, which is more versatile than the state of the art tools already available.

V. CONCLUSION

The diagnostic capacity of the system described in this work aligned with the evaluations of expert radiologists and therefore presented enormous potential as a critical resource in the management of the COVID-19 pandemic. The use of our own database, together with the application of transfer learning techniques with DenseNet-121 and the implementation of advanced metrics such as Mcc, further strengthened the reliability and applicability of the system. Despite these advances, we must acknowledge that the system is in the early stages of development and that in the future, intensive clinical validations in real settings will be required prior to its clinical use to ensure the robustness and generalisability of the proposed system. In any case, COVID-19 is currently under control and it seems unlikely that new waves of infection like those experienced in 2022 and 2023 will occur again. Thus, to a certain extent, this makes it difficult to execute validation tests for this current proposal in real environments. Nonetheless, this is not a problem because the system could be useful in possible future pandemics and could be adapted for other diseases or pneumonias of other aetiologies with similarities in terms of their radiological presentation. If such validation is possible, cost-effectiveness analyses should also be undertaken in the future to understand the real benefit associated with its use. In turn, the interpretation of DL models and confidence in their results is an area that will require continued attention, suggesting that AI explainability methods should also be explored. In future work we plan to integrate a new module into this system which will employ techniques to make its predictions more robust and explainable. Hence, we hope that combining these techniques with the specific knowledge of specialists will lead to consistent clinical interpretations that will positively impact decision-making processes and generate more confidence among clinicians, thereby favouring its use.

GLOSSARY OF ACRONYMS AND ABBREVIATIONS

- Airspace opacity severity: ASOS
- Anteroposterior: AP
- Artificial Intelligence: AI
- Area under the curve: AUC
- Chest X-ray: CXR
- Convolutional Neural Networks: CNNs
- Deep learning: DL
- Digital Imaging and Communication In Medicine: DICOM®
- False negatives: FN
- False positives: FP
- Intensive care unit: ICU
- Matthews correlation coefficient: Mcc
- Picture Archiving and Communication System: PACS
- Pneumonia risk: PR
- Polymerase chain reaction: PCR
- Posteroanterior: PA

- Receiver operating characteristic: ROC
- Root mean square error: RMSE
- True negatives: TN
- True positives: TP

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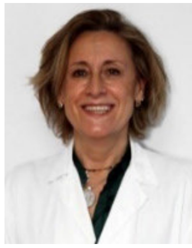

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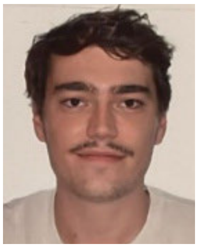

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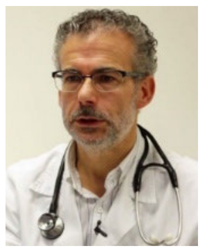

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