Article **Journal of Physiotherapy and Medical Technology**
December, 2023 Vol.7 No.18 15-27

Artificial intelligence in the prevention of respiratory distress syndrome

Inteligencia artificial en la prevención de síndrome de dificultad respiratoria

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DOI: 10.35429/JP.2023.18.7.15.27 Received September 10, 2023; Accepted December 30, 2023

Abstract

Malformations in fetal development affect the health of the product and the mother. Preventing illnesses during gestation, allows for a healthy and dignified life at birth. Data from INEGI in its report on Fetal Death Statistics (EFD) 2022, show that in Mexico there is an average of 72.2 fetal deaths per 100,000 women of childbearing age. Of these deaths, 25,041 deaths were registered during the year 2022. 5950 deaths correspond to gestational disorders, respiratory or cardiovascular disorders and congenital malformations. Lung defects result in induced abortion or Respiratory Distress Syndrome (RDS). RDS can be prevented by clinical studies and radiological criteria. Identification of abnormal developments using digital analysis of lung images during pregnancy can help identify a defect. We propose ONE classification tool using deep learning in a multiclass categorization of bronchopulmonary sequestration, cystic malformations and diaphragmatic hernia, where there is a risk of defect appreciation and thus misjudgment leading to complications or death. Resulting in a model accuracy of 88.88%, out of a set of 42 two-dimensional sonograms.

Malformation, Fetal lung, Artificial Intelligence

Resumen

Las malformaciones en el desarrollo fetal, afectan a la salud del producto y la madre. La prevención de padecimientos durante la gestación, permite que al nacer se tenga una vida digna y saludable. Datos del INEGI en su informe de Estadísticas de Defunciones Fetales (EFD) 2022, muestran que en México hay un promedio de 72.2 muertes fetales por cada 100,000 mujeres en edad fértil. De esas muertes, 25,041 defunciones fueron registradas durante el año 2022. 5950 decesos corresponden a trastornos en la gestación, trastornos respiratorios o cardiovasculares y malformaciones congénitas. Los defectos pulmonares, resultan en aborto inducido o en el Síndrome de Dificultad Respiratoria, RDS del inglés de Respiratory Distress Syndrome. RDS puede prevenirse por medio de estudios clínicos y criterios radiológicos. La identificación de desarrollos anormales usando el análisis digital de imágenes de pulmones durante el embarazo, puede ayudar a identificar un defecto. Proponemos una herramienta de clasificación usando aprendizaje profundo en una categorización multiclase de secuestro broncopulmonar, malformaciones quísticas y hernia diafragmática, donde existe riesgo de apreciación del defecto y por ello una valoración errada que lleve a complicaciones o el fallecimiento. Resultando en una exactitud del modelo de 88.88%, de un conjunto de 42 sonogramas bidimensionales.

Malformación, Pulmón Fetal, Inteligencia Artificial

Citation: PÉREZ-ESCAMILLA, Javier, MENDOZA-GUZMÁN, Lorena, CRUZ-GUERRERO, René and PÉREZ-BATISTA, Mario. Artificial intelligence in the prevention of respiratory distress syndrome. Journal of Physiotherapy and Medical Technology. 2023. 7-18: 15-27

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Introducción

The health of the population is a concern in recent years for developing countries, as it has positioned itself as an incident factor in human, economic and social development. It is important for medical centers and health institutes to strengthen technological tools to support medical diagnosis in a fast and non-intrusive way. It is especially important to bring non-invasive diagnostic services closer to vulnerable and low-income populations. Therefore, computer vision techniques in conjunction with machine learning tools, strengthen the task of health personnel to mitigate the risks arising from a condition. Respiratory Distress Syndrome (RDS) is a condition that can be prevented by analyzing the Fetal Pulmonary Maturity (FPM) study within the gestational development period. The search for safe methods, which do not threaten the health of the product and the mother, is presented as an opportunity for research in the face of traditional procedures.

Ultrasound is a medical tool that has the advantage of being a non-invasive and safe method that supports health personnel in the detection of anomalies. The FPM study is applied to images in JPEG format, where the differentiation of tissue and the week of gestation enables the physician to make a diagnosis of pulmonary development, allowing to assess whether there is any organ or tissue involvement. 15 million infants are born each year with a deficiency. A group of these are premature infants in gestational stages of up to 37 weeks of the recommended 40 weeks. 45% of all deaths of infants under 5 years of age, between 60% to 80%, are premature infants, according to data from the World Health Organization (WHO) in the "WHO recommendations for the care of premature or low birth weight infants", highlighting that the highest mortality is due to respiratory deficiencies. (World Health Organization, 2022)

In Mexico, according to data from the National Institute of Statistics and Geography, INEGI, the statistics of deaths in the fetal stage has a rate of 6.7 women of childbearing age per 10,000, where in the year 2021 a total of 23,000.00 deaths were registered, of which 2,016 are due to respiratory problems (National Institute of Statistics and Geography, 2022).

The number of deaths may be higher than those reported, considering that the report does not specify deaths due to malformation located in one or both lungs and/or resulting in induced abortion or RDS. The prevention of RDS can be supported by clinical studies and/or radiological criteria. Clinical analysis is an invasive method that relies on the levels of lecithin/sphingomyelin contained in the amniotic fluid, representing a low risk of serious complications derived from the extraction, but not zero. Radiological analysis, on the other hand, is a non-invasive method where the physician performs an assessment of fetal lung development by means of lung ultrasound.

If there is any doubt in the diagnosis by radiological method, the clinical method is applied or both, if the health personnel consider so. The problem with ultrasound diagnosis lies in the ability to identify aspects of the image analyzed, such as shape, size, among others. Misdiagnosis by visual means may result in medication that puts the life of the fetus at risk. The criteria of the WHO and the Pan American Health Organization focus on promoting diagnosis by non-invasive methods for health care in pregnant women.

The WHO considers the prevention of fetal and maternal health to be a focus of attention in the countries of the Americas. In order to mitigate risks and reduce deaths, it has established that ultrasound is the method that can meet the challenge. Being a method that can be improved and together with other radiology services be key in early detection (Pan American Health Organization, 2015).

Congenital malformations affect intrauterine life, for the correct diagnosis non-invasive techniques are required, this is where the ultrasound study can facilitate monitoring and care. An expert has the ability to find deficiencies in body parts, such as damage to the nervous system, spina bifida, gastroschisis and microcephaly to mention a few. In addition to fetal deficiencies, it highlights the importance of medical follow-up, where prevention in the early stages of development is easier (Espinosa Arreaga & Lucio Aldaz, 2020).

The prevention of pulmonary complications in newborns is a focus of attention in neonatal mortality, caused by pulmonary surfactant deficiency.

Therefore, non-invasive techniques present the opportunity to predict respiratory morbidity, so the evaluation of pulmonary maturity has shown that an algorithm can predict the occurrence of RDS, respiratory deficiency syndrome (Albinagorta Olórtegui, 2022).

The terms used to describe the human body, where health experts and anatomists use imaginary planes that cut or section the anatomical position, can be roughly categorized as: coronal, sagittal and transverse. They are detailed in subtypes specific to a localized area. Table 1 describes the sub-planes that can be used for precise sectioning (Kenhub, 2023). Figure 1 shows an example of the body planes. Figure 2 and Figure 3 show examples of transverse and sagittal plane ultrasound scans.

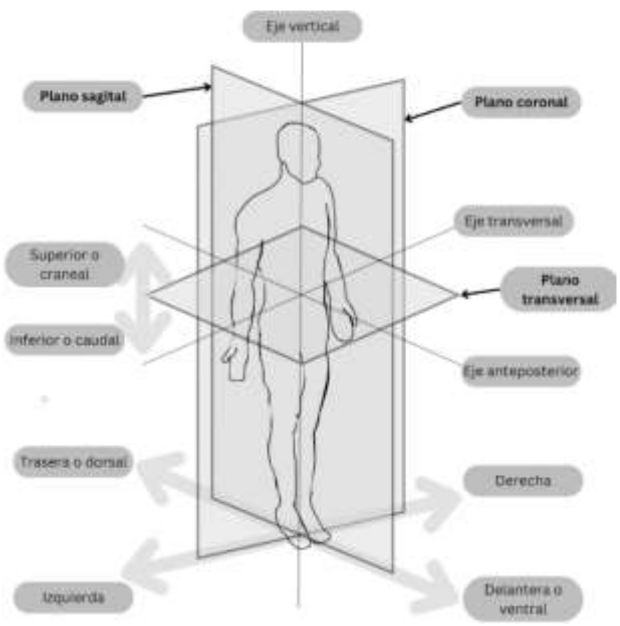

Figure 1 Anatomical planes
Own Creation

Here the planes become relevant when used in ultrasound studies and the interpretation of the sonogram or ultrasound, since the position is relative to the plane and in reverse order to the medical staff.

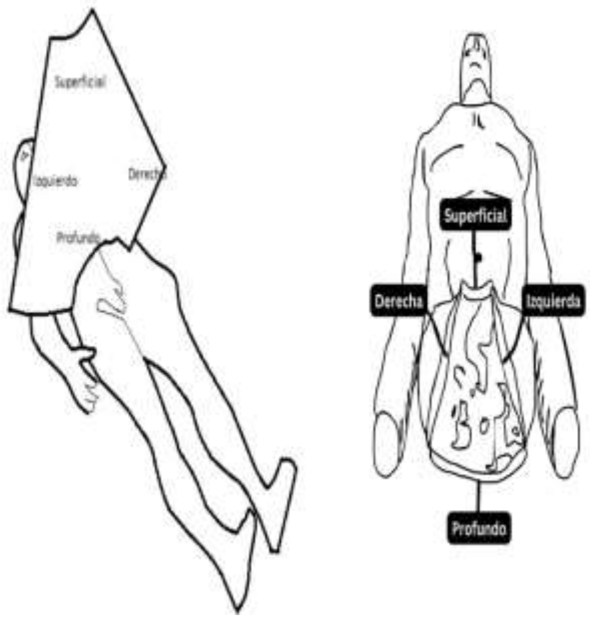

Figure 2 Cross section
Own Creation

The image is interpreted with the assumption that it is positioned below the patient and will be viewed upward from the patient's feet. The graphic shows the abdomen of the patient, the reverse of the medical staff view is displayed, the left side shows the right side of the patient while the right side shows the left side of the patient. The upper part shows the front region of the abdomen and the lower part shows the posterior region of the abdomen.

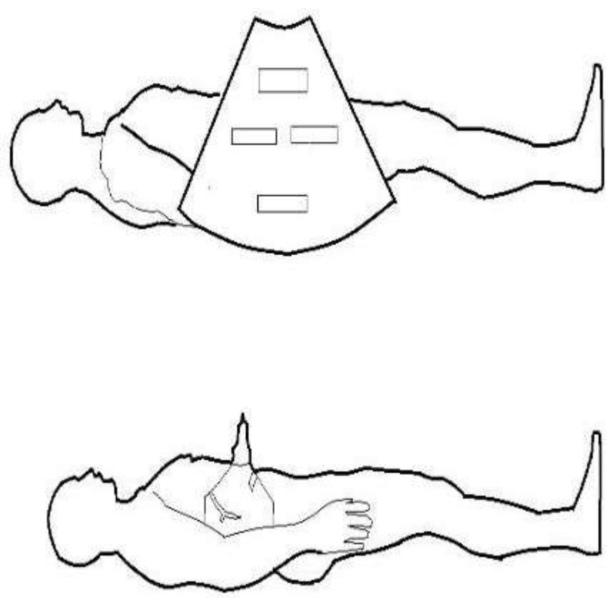

Figure 3 Longitudinal section
Own Creation

In longitudinal sections, the upper part represents the head and the lower part represents the posterior part of the body. The left side of the image shows the part closest to the front of the abdomen, while the right side shows the far side.

This is similar to looking at slices through a patient from the right side.

	Anatomical planes
Anterior	In front of or in front of
Posterior	To the rear of or behind
Ventral	To the front of the bod
Dorsal	Toward the back of the body
Distal	Away or farther than another from the trunk or the point of origin of this one
Proximal	Closer to the trunk or toward the trunk, or to the point of origin of this
Middle	Midline of the body
Medial	Towards the midline
Lateral	Away from or away from the midline
Superior	Towards the top of the head
Lower	Towards the feet
External	Towards the surface, superficial
Internal	Away or away from the surface, deep
Frontal	Toward the anterior portion of the brain
Occipital	Toward the posterior portion of the brain
Coronal plane	Vertical plane dividing the body into anterior and posterior
Sagittal plane	Vertical plane that divides the body into left and right
Transverse plane	Horizontal plane dividing the body into superior and inferior

Table 1 Type of anatomical planes

The different planes that can be used to obtain a reference and image of the human body are described.

Ultrasound is a sound wave test. It allows an exploration of the internal organs of the human body, it is also called ultrasound or sonography. It is used to monitor fetal health during the gestation period. In addition, it is an efficient support to diagnose soft tissues, such as glands and blood vessels. It also serves as a support for other invasive procedures (Biblioteca Nacional de Medicina, 2023).

The echo occurs when a sound hits a reflective surface, so the resulting vibration returns to the focus. Several effects occur: reflection, which is when the wave travels through a given acoustic impedance of the medium; acoustic interface, which is the relationship between the two media; acoustic impedance, which is the resistance to the passage of waves through a fabric; propagation velocity, where impedance is directly related to the density of the medium; acoustic shadow, which is the sound that is totally reflected.

Refraction, which is the sound that changes direction upon contact with the reflecting medium; attenuation, which is the loss of energy of the signal; ultrasound beam, which is the damping of the wave by means of divergences and dispersion. The resolution of an ultrasound scanner is determined in axial and lateral type, depending on the ability to produce two different and distinguishable echoes between two structures or interfaces close to each other (Segura-Grau et al., 2013).

Ultrasound modes allow analysis of aspects during gestation, depending on the type diverse information can be obtained. A-mode is an ultrasound modality that is used to represent the amplitude of ultrasonic waves as a function of time, the horizontal axis represents time, while the vertical axis represents the amplitude of the ultrasonic waves, commonly used to obtain accurate measurements of distances and depths of structures. B-mode, also known as B-mode ultrasonography, is a medical imaging technique that uses ultrasound waves to generate real-time images of internal body structures.

Here, two-dimensional images depicting tissue anatomy are obtained. Mode C, also known as "contrast mode," is used to enhance the visualization of certain structures or areas within the body, where the use of ultrasound contrast agents improves the quality of the images obtained. The Doppler mode is based on the change in frequency of sound waves reflected by a moving object, in this case, blood cells in the bloodstream. A color code is used to represent the direction and speed of blood flow. For example, red may indicate blood flow toward the transducer, while blue may indicate blood flow away from the transducer. It allows clinicians to visualize the distribution of blood flow in real time. (Standen, 2022).

Ultrasound is a medical tool that has the advantage of being a non-invasive and safe method that supports health personnel in the detection of anomalies. The study is used on images in DICOM or JPEG format, where the differentiation of tissue and the week of gestation, enables the physician to make a diagnosis of the development of organs and the fetus in general.

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This project proposes the development and implementation of a software application that allows health personnel to process a neonatal lung ultrasound, apply artificial vision techniques and obtain a characterization of the percentage of soft mass in development. Thus, to obtain a classification and labeling of the image to support the diagnosis or search for lung malformations resulting in RDS or miscarriage.

Background

During the gestational period, malformation of non-functional bronchial tissue, called Bronchopulmonary Sequestration (BRS), may occur. Routine morphologic ultrasound at 20 weeks makes early detection of the condition possible. It is a mass that is described as a non-utilitarian tissue, which does not connect with the tracheobronchial tree and is connected by means of an aberrant system artery, originating from the descending aorta. It is an anomalous development of the pulmonary artery, which can drain systemically.

This portion of additional pulmonary parenchyma is considered to be a solid, hyperechogenic, homogeneous mass occupying the pulmonary lower lobe. Figure 4 illustrates BRS Although it is considered a benign lung tumor, the criteria of size, growth rate, degree of cardiac or pulmonary compression, existence of hydrothorax or fetal heart failure. Physically, the evaluation of the tissue is based on maximum diameter in length, transverse and antero-posterior multiplied by 0.52 and divided by the cephalic circumference. Thus an index greater than 1 is of high risk, while one less than 1 has to be involute and can be treated after birth. (Cruz-Martínez & Ordorica-Flores, 2019).

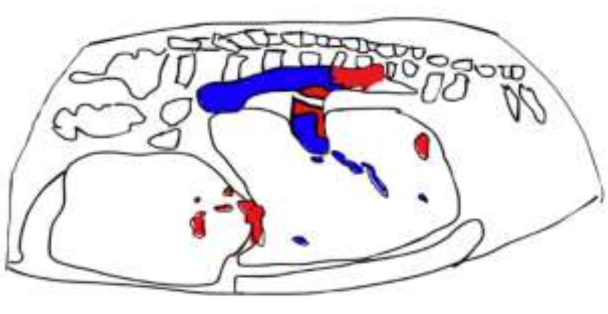

Figure 4 Sagittal cut ultrasound of fetal thorax. The image shows the solid mass corresponding to SBR, connected to the abdominal aorta
Source: https://www.scielo.org.mx/img/revistas/gom/v87n2//0300-9041-gom-87-02-116-gf1.png

During fetal lung development, lesions can be generated that are part of a group of anomalies based on dysplasia in the embryonic formation of the pulmonary tree, Figure 5. Among these is the adenoid cystic pulmonary malformation (ACM), where the classification is based on lung cysts ranging from two centimeters in single cysts, cysts smaller than one centimeter, and micro-cysts. Medical diagnosis is based on fetal lung morphologic assessment. An important feature of diagnostic differentiation between bronchopulmonary sequestration, bronchogenic cysts and diaphragmatic hernia is whether a nutritional vessel is present. A differential study to determine the condition is required. In ACM iit is characteristic that there is no irrigation connection. The evolution of the cysts triggers the phenomenon of hydrops and eventually fetal death (Vega, et al., 2015).

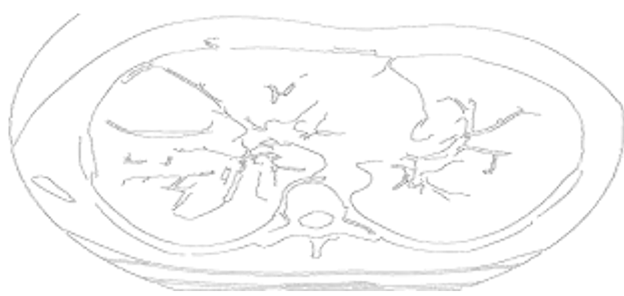

Figura 5 Ultrasound shows a macrocystic
Source: https://www.chop.edu/conditions-diseases/congenital-cystic-adenomatoid-malformation-ccam

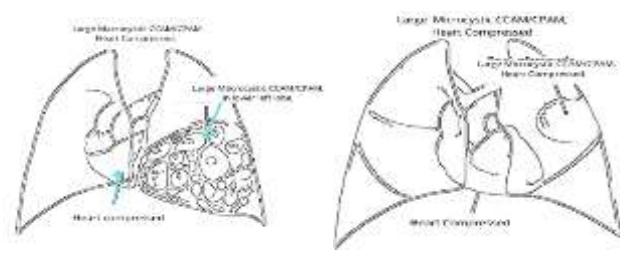

Figura 6 *Congenital cystic adenomatoid malformation (CCAM) is a benign lung lesion that appears before birth as a cyst or mass in the chest*
Source: https://www.chop.edu/conditions-diseases/congenital-cystic-adenomatoid-malformation-ccam. In those cases

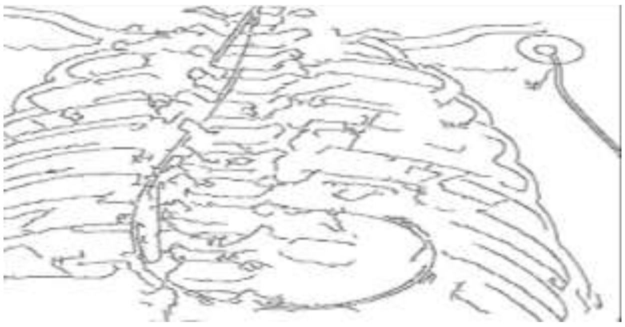

Figure 7 Plain chest x-ray of a patient with congenital diaphragmatic hernia. Hydro Aerial images of intestinal loops in the left hemithorax with deviation of the mediastinal structures to the right side were observed. The nasogastric tube shows that the stomach is in the chest
Source: https://enfermeria.top/apuntes/pediatria/hernia-diafragmatica-congenita/

Among the studies for lung maturity are the traditional ones, such as: a) lamellar body count, b) lecithin/sphingomyelin ratio, c) presence of phosphatidylglycerol, d) optical density of lamellar bodies and e) foam stability index (Clements test). The QuantusFLM ultrasound method is a tool that uses digital image pre-processing techniques to extract textural features and machine learning algorithms to predict the risk of respiratory morbidity. In practice, the traditional amniotic fluid procedure (b) and the sonogram procedure obtain the best clinical results (Zuñiga Vico, Gila Sánchez, & Hurtado Sánchez).

Pando García (2020) performed a quantitative study of the QuantusFLM method to predict MPF using the metrics of accuracy, specificity, sensitivity and negative predictive value, obtaining 87%, 86%, 91% and 98%. The invariance in ultrasound acquisition (position, illumination, shadows, resolution), allows the extraction of image texture features in a region of interest (ROI). In this ROI it will correspond to the fetal lung tissue. Once similarities of the inputs can be detected, a classifier can be trained for the task of PFM detection.

(Hernández Sancho & Rojas Maruri, 2020), who medically treat a pulmonary sequestration, make the diagnosis by means of ultrasound techniques, in this case echocardiography. Through visual analysis, they identify aortic stenosis and moderate aortic coarctation, with dilatation of the left atrium.

Through observations in the sonogram, they were able to predict the risk of intralobar RBS with basal cysts of one to two cm (AML), in addition to the presence of an aberrant aortic nutritional vessel of supra celiac origin in the abdominal aorta. The correct identification of the parts allowed an adequate intervention.

Deep learning, a vector-based technique, is based on a point in geometric space. The inputs are converted into an initial vector space and there is a target vector space. Geometric transformations are performed by the processing layers on the input data. The geometric complexity increases between layers, but is decomposed into simple transformations. That is, the input space is mapped into the target space, point by point. The process is parameterized by the synaptic weights, directly related to the performance of the model. The differentiation of each plane allows us to learn its parameters. A widely used optimization technique is the gradient descent, being a smooth and continuous decomposition. Deep learning models are machines for decomposing high-dimensional data manifolds (Collet, 2017).

Computer vision is a set of image processing and pattern recognition techniques, artificial intelligence and computer graphics. The input is based on digital images, the objective is to obtain information through descriptions based on feature extraction. The output of the process is the understanding of the scene. It can focus on tasks such as enhancement or recognition, being dependent on computational technology.(Wiley & Lucas, 2018).

For classification tasks categorical data consist of discrete labels, when working in machine learning, it is usually necessary to convert these categories into numerical values before entering them into a model. One-hot encoding, a common technique used to represent categorical variables, is represented as a binary vector, where only one element is set to one (1), indicating the presence of the category. Most encoded vectors will consist of zeros, resulting in a large amount of wasted memory. The sparse representation of categorical data, aims to address this inefficiency by using an integer index to represent each class. (Brownlee, 3 Ways to Encode Categorical Variables for Deep Learning, 2020).

ISSN 2523-6849

Deep learning models require tuning, so "Categorical accuracy" is a metric that measures the accuracy of predictions by calculating the fraction of correctly classified samples in the training dataset. "Value Categorical Accuracy" is used during the validation phase of training, it measures the accuracy of model predictions on a separate validation dataset, which is not used for training. This helps you evaluate how well the model generalizes to new and unseen data (Brownlee, How to Use Metrics for Deep Learning with Keras in Python, 2020). "Loss", and "Value Loss", help determine how performance changes over epochs and support diagnosing any problems with learning (Stefania, 2023).

The "Sensitivity" and "Specificity" values are the ratio of positive and negative classification per class. In AUC, sensitivity and specificity are related distributions, where the overlapping areas between them indicate the model's ability to discriminate (Brownlee, Sensitivity Analysis of Dataset Size vs. Model Performance, 2021).

Models in deep learning, are shown in Figure 8, Figure 9, Figure 10, Figure 11 and Figure 12 AlexNet

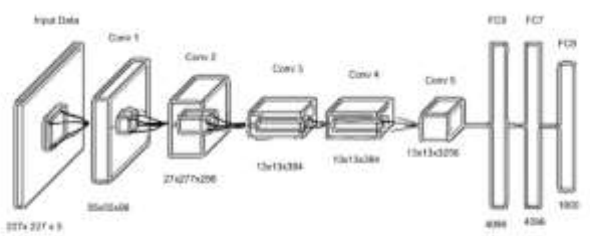

Figure 8 AlexNet model architecture
Source: https://www.mdpi.com/2072-4292/9/8/848/htm?ref=https://githubhelp.com

The model uses five convolutional stages, then flatten the vector resulting for classification.

Figure 9 VGG16 Architecture
Source: https://www.academia.edu/download/68916518/IRJET_V8I3564.pdf.

The Visual Geometry Group 16 model is more compact than Alexnet, the dense layers are used for classification.

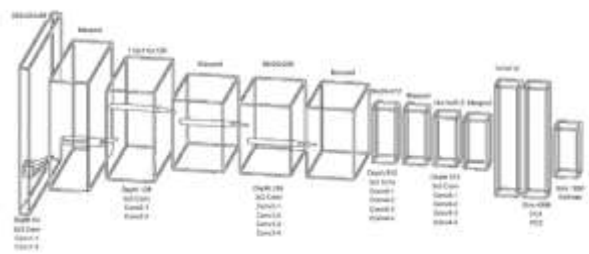

Figure 10 VGG19 Architecture
Source: https://cdn.techscience.cn/uploads/attached/file/20201030/20201030055352_36147.pdf.

Unlike some architectures that use filters of different sizes, Visual Geometry Group 19 uses 3x3 filters in all convolutional layers. This provides uniformity and simplicity in the architecture.

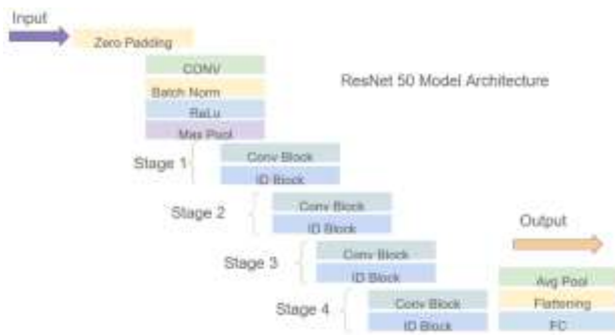

Figure 11 RESNET 50 Architecture
Source: https://cdn.techscience.cn/uploads/attached/file/20201030/20201030055352_36147.pdf

The distinguishing feature of ResNet is the use of residual blocks that allow layers to learn identity functions, which facilitates the training of much deeper networks. ResNet-50 specifically has 50 layers in total, including convolutional, clustering and fully connected layers.

Inception V3

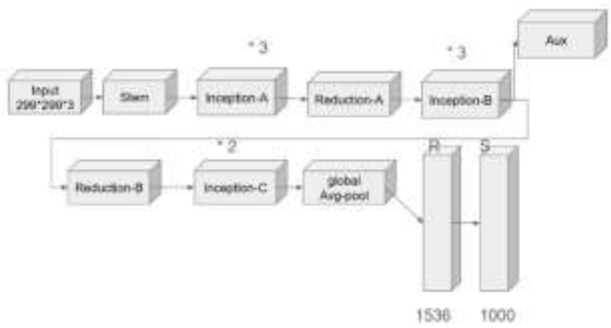

Figure 12 Inception V3
Source: https://medium.com/@AnasBrital98/inception-v3-cnn-architecture-explained-691cfb7bba08.

Known as GoogLeNet, the Inception architecture is characterized by the use of "Inception" blocks containing multiple convolutions of different kernel sizes. These blocks allow the network to capture patterns of different spatial scales in parallel, thus enhancing the network's ability to learn more complex and richer representations.

Methodology

A quantitative review of several neural networks was performed, using Tensorflow and transfer learning techniques. The objective is the classification of three medical diagnoses that, without attention, can lead to fetal death or RDS. Automated feature extraction functions are used, in conjunction with preset techniques for taking radiographs, on an ROI as the object of study. It focuses on the detection of abnormal conditions in the MPF. The three conditions to be treated are: BRS, AQM and diaphragmatic hernia (DH). Figure 13 illustrates the process.

Identify aspects of ultrasound: through documentary research, aspects of the anatomical planes and cuts used in the cases reported in the literature were identified. In addition, the acquired knowledge of the ultrasound acquisition methods and technical details of the operation of the machines that generate the sonograms were expanded.

Image selection: the criteria used to select the sonograms that are part of the research are: presence of any condition associated with the three diagnoses mentioned; the type of anatomical plane, either in axial or longitudinal section.

The size of the image, minimum 96 dpi and 24 bits of color in at least 100x100 pixels.Using the web scraping technique, images were located and selected for investigation. The use of the sonograms obtained is academic in scope.

Input preprocessing: The inputs were transformed into arrays of 227 by 227 pixels and three color channels. Finally, an image normalization process was performed.

Categorization: a multiclass categorization technique (one-hot encoding) was implemented on the dataset in order to use classification, resulting in three encodings: 0 0 1 = DH, 0 1 0 =AQM, and 0 0 1 = BRS.

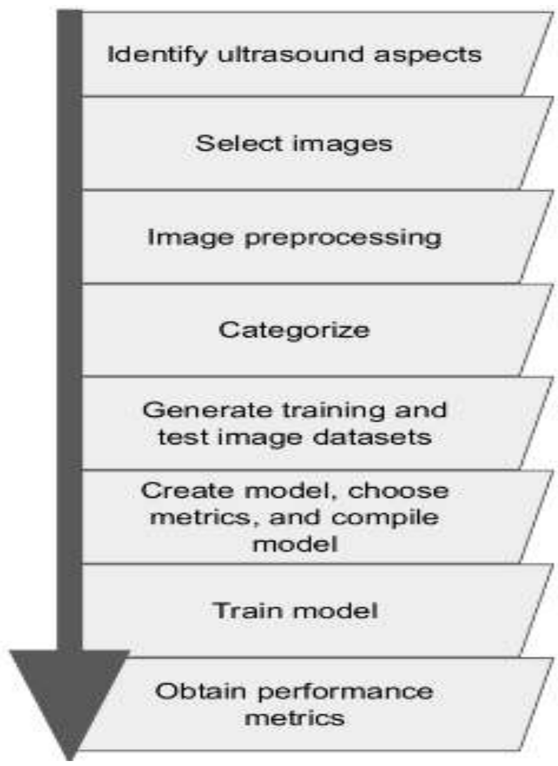

Figure 13 Implementation process, own creation. It starts with the collection strategy, image selection, image pre-processing, class categorization, creating the necessary sets, establishing the model, compiling the model and obtaining the necessary metrics.

Training and test set: the indices of each sonogram were randomized using s and with the Scikit-learn library the training and test set was created in a ratio of 80%-20%.

ISSN 2523-6849

Create model, select metrics and compile model: using TensorFlow and Keras software via Transfer Learning, several AlexNet deep network models were implemented: a) using all pre-processing layers, b) with brightness and contrast pre-processing and c) without pre-processing, whose optimization setup is stochastic gradient descent method based on adaptive "adam" estimation. The metrics selected for training and validation are shown in Table 2.

Training	Validation
Categorical Accuracy	Value Categorical Accuracy
Loss (Categorical cross entropy)	Value Loss
AUC (Area Under Curve)	
Sensitivity	
Sensitivity	

Table 2 Model metrics.Training and validation metrics help fine-tune the model

Training model: For training, 1000 epochs were used, using a subsampling of 8 and derived from the fact that there are few images, the test set was used in order to avoid overtraining.

Performance metrics: Finally, the prediction of all models was run to obtain the metrics, which are shown in the results section.

Results

Obtain Performance metrics: Finally, the model prediction was run to obtain the metrics, which are shown in the results section. The macro performance of the model, using variants in the preprocessing are shown in Table 3.

Model	Categorial Accuracy	AUC
Alexnet	88.89%	88.87%
EfficientNetB0	55.50%	77.22%
DenseNet121	55.56%	81.48%
InceptionResNetV3	55.55%	56.84%
Resnet 50	55.56	61.73%

Table 3 Performance metrics

The result for each model was made with the same parameters for the training and same training and test dataset..

The set of images during the investigation is illustrated in Figure 14. The sonograms were obtained by web scraping and are intended for academic purposes.

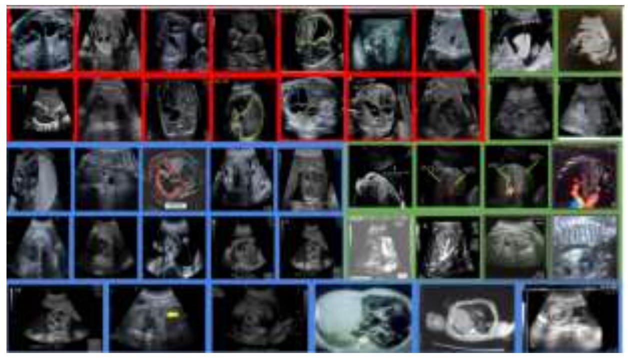

Figure 14 Data set

On the left, diaphragmatic hernia. In the center, adenoid cystic pulmonary malformation. On the right, bronchopulmonary sequestration. The sonograms that were selected contain the pulmonary lesion.

AlexNet, without preprocessing, was trained for 1000 epochs, where the monitoring graph was obtained, which is illustrated in Figure 15. The best result obtained was 88.88% categorical accuracy and an area under the curve value of 90.43%. Table 4 shows the results obtained.

Metric	With Layers	Contrast	Without pre processing
Categorical Accuracy	55.56%	77.77%	88.88%
Pre - processing layers	Rotation= (-0.2,0.3) Flip= Horizontal and Vertical Brightness = [-0.8, 0.8] Translation= Higher=0.2, Anchor= 0.2	Contrast=[0.1, 0.4] Brightness = [-0.8, 0.8]	NA

Tabla 4 Alexnet with and without processing layers

The pre-processing layers did not support a better result. The highest accuracy is obtained with the model without processing.

The values during training are shown in Figure 15. Performance metrics were captured for 1000 epochs.

ISSN 2523-6849

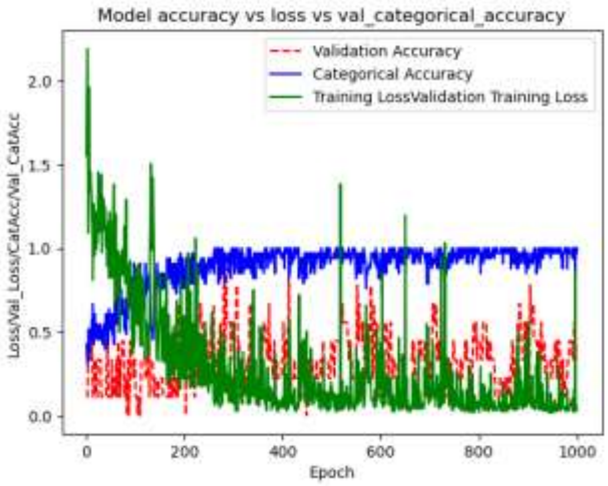

Figure 15 Plot of categorical accuracy versus categorical accuracy value versus loss

At epoch 378 it obtained its best performance (88.88%). Subsequent iterations no longer reflect further learning.

Metric	Precision	Recall	F1 Score	Support
DH	1.0	1.0	1.0	5
AQM	1.0	0.80	0.89	1
BRS	0.75	1.0	0.86	3
micro Avg	0.89	0.89	0.90	9
micro Avg	0.92	0.93	0.92	9
weighted Avg	0.89	0.89	0.89	9
samples Avg	0.89	0.89	0.89	9
For DH precision 1.0				
For AQM Precision 1.0				
For BRS 0.75				
Macro Precision 0.92				

Table 5 Macro, weighted and macro results

The values obtained can be assumed that the model discriminates moderately well.

The confusion matrix of the model is shown in Figure 16.

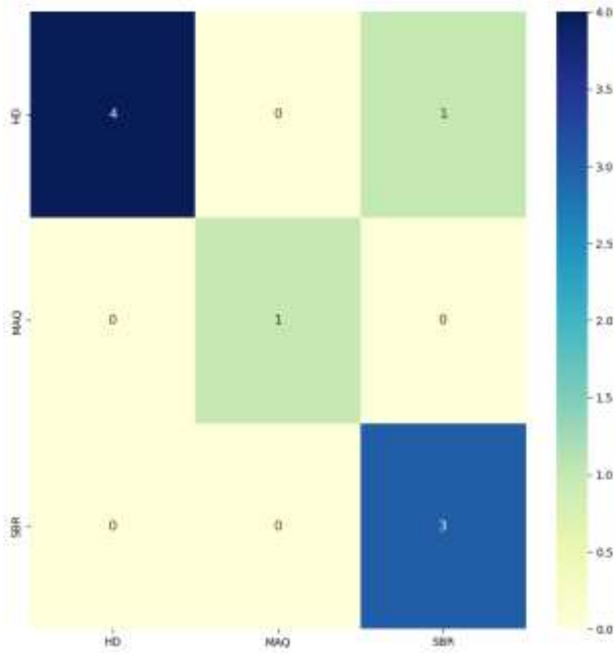

Figure 16 Confusion matrix

Illustrates the classification of each condition in the prediction.

The ModelCheckpoint method of the Keras callbacks class was used to save the synaptic weights, depending on the best performance of the categorical accuracy value. It can also be used to stop the training early, if the performance on the validation set starts to degrade.

For model prediction, the images shown in Figure 16 were used. Each of the sonograms belongs to a class, in this case a categorical value.

Figure 16 Test set. Each image belongs to a class: 0 0 1 = DH, 0 1 0 =AQM, 0 0 1 1 = BRS. All elements were classified correctly

A comparison of the results in the proposed method and a QuantusFLM diagnostic method is given in Table 6.

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Metric	AlexNet without pre processing	QuantusFLM
Macro Precision	92.00%	1.0
Accuracy	88.89%	NA
AUC (Area under curve)	88.27%	NA
Specificity	94.44%	86.00%
Sensibility	88.89%	91%

Table 6 Comparative to Metrics of QuantumFLM

The results obtained have values close to those of the quantumFLM method.

Conclusions

According to (Vega, et al., 2015), to discriminate between SBR, MAQ and HD, a differential study is required. Therefore, the work contributes to facilitating the identification of the condition, for rapid treatment. Being a non-invasive method, ultrasound becomes relevant as a means for diagnosis comparable to other invasive methods according to (Zuñiga Vico, Gila Sánchez, & Hurtado Sánchez).

The underpinning of the performance of the proposed model, is given that each sonogram contains the features that the network is able to perceive to discriminate between each condition, as anticipated by (Wiley & Lucas, 2018). The different options of the pre-processing, showed no better result than the model without pre-processing. This characteristic may be associated with the fact that the devices that generate the sonograms already make adjustments such as contrast and brightness. The specific techniques for sonogram capture are beyond the scope of this work.

In Figure 15, the plot shows instability in training, since it is not a smoothed line and that the optimizer used in training is "adam" as anticipated by (Collet, 2017). One of the causes is that the size of the training data is small and may not represent all the input data. The variation in the image may be derived from the input decomposition, since it is an unsupervised process. In example, if the input vector is decomposed and matched with the target vector, another input is not matched. For this the categorical accuracy value metric, supports in visualizing how the neural network is performing on the validation data and checking for over-fitting.

An over-fit model performs well on the training data, but poorly on the validation data. In general it implies that the neural network, at some epochs over fits and at other epochs under fits for both sets. The best result is not necessarily the one with the highest accuracy, but according to Table 4, it would be the one that best discriminates between classes and is not over-fitted.

Ultrasound mode B helps to obtain a two-dimensional sonogram, doppler mode helps to identify blood vessels. The latter is useful to detect cystic malformations and bronchopulmonary sequestration. How to take the sonogram is not covered in this publication. It will be dealt with in a later investigation.

The AUC value obtained reflects the ability of the model to discriminate between classes. However, in this proposal, we work under the assumption that there is suspicion of disease. Therefore, we do not deal with cases where no condition is present. This will be addressed in another paper.

Validation metrics are useful so that the model can be adjusted, Keras tools make it easier to keep the training supervised. It is useful to consider a value to monitor the performance of the model on the training data and guide the optimization process. Adjustments, such as pre-processing layers, can improve performance. Augmentation of the data will not in all cases give the best result, but it comes close. The goal is to increase the categorical accuracy during training by adjusting the model parameters, either in subsampling, or by re-arranging the ensemble.

The use of the model is recommended to support specialists in the medical area and for didactic use.

The difficulty of obtaining sonograms is based on two aspects: a) data protection and privacy laws, b) the difficulty of associating with health institutions. The first raises the challenges of data use and limitations. The second focuses on project time, budget availability, lack of personnel and initiative to participate.

Acknowledgments

We thank the Master 's program in Computer Systems of the ITS del Oriente del Estado de Hidalgo (ITESA) and the educational program of Engineering in Computer Systems of the ITS del Occidente del Estado de Hidalgo. Also, Eduardo Daniel Montufar Romero for the revision on the English language revisions of this work.

Financing

This work was financed by the Tecnológico Nacional de México (TECNM) and the state of Hidalgo through the software engineering and distributed systems research line of the ITS del Occidente del Estado de Hidalgo and the ITS del Oriente del Estado de Hidalgo.

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