Transfer Learning to improve the Diagnosis of Type 2 Diabetes Mellitus (T2D)

Transfer Learning para mejorar el Diagnostico de Diabetes Mellitus Tipo 2 (T2D)

CUTIÉ-TORRES, Carmen†*, LUNA-ROSAS, Francisco Javier, LUNA-MEDINA, Marisol and DUNAY-ACEVEDO, Cesar

TecNM/Instituto Tecnológico de Aguascalientes, Departamento de Sistemas y Computación, Av. A. López Mateos 1801 Ote. Fracc. Bona Gens, Aguascalientes, Aguascalientes, México. C.P. 202564
Universidad Autónoma de Aguascalientes, Centro de Ciencias de la Salud, Av. Universidad # 940 Col. Universitaria C.P. 20131, Aguascalientes Ags., México

ID 1st Author: *Carmen, Cutié-Torres* / **ORC ID:** 0009-0000-9210-5667, **CVU CONAHCYT ID**: 1156355

ID 1st Co-author: *Francisco Javier, Luna-Rosa* / **ORC ID:** 0000-0001-6821-4046, **CVU CONAHCYT ID:** 87098

ID 2nd Co-author: *Marisol, Luna-Medina* / **ORC ID:** 0009-0006-0188-9317, **CVU CONAHCYT ID:** 1303944

ID 3rd Co-author: *Cesar, Dunay-Acevedo* / **ORC ID:** 0009-0001-9370-2997, **CVU CONAHCYT ID:** 1303869

DOI: 10.35429/EJDRC.2023.16.9.9.21 Received March 28, 2023; Accepted June 30, 2023

Abstract

Transfer Learning is a Deep Learning technique that is currently being used in early and non-invasive diagnosis of T2D. The objective of this work is to design and implement a Transfer Learning model trained with images of skin patches belonging to healthy people and diabetic foot patients. The research methodology was constituted by 3 phases (Analysis and Design, Development and Evaluation) composed of 5 steps that comply with the proposed objective. Several convolutional neural network (CNN) models were developed: CNN built from scratch, AlexNet, CNN with data augmentation technique, FE-VGG16, FE-ResNet50 and FT-VGG16. These models were evaluated using a set of metrics derived from the confusion matrix, the Receiver Operating Characteristic curve (ROC) of each model and the value corresponding to the area under the curve (AUC). The best performance corresponded to FT-VGG16 model that fuses VGG-16 pretrained model with a block of fully connected layers. Finally, satisfactory results are reported and allow us to conclude that the application of Transfer Learning models for the classification of diabetic foot images constitutes a viable tool for the non-invasive diagnosis of T2D.

Transfer Learning, Classification, Diagnosis

Resumen

Transfer Learning es una técnica de Aprendizaje Profundo que está siendo utilizada actualmente en el diagnóstico temprano y no invasivo de T2D. El objetivo de este trabajo es diseñar e implementar un modelo de Transfer Learning entrenado con imágenes de parches de piel pertenecientes a personas sanas y enfermos de pie diabético. La metodología de la investigación se constituyó por 3 fases (Análisis y Diseño, Desarrollo y Evaluación) compuestas por 5 pasos que dan cumplimiento al objetivo propuesto. Se desarrollaron 6 modelos de redes neuronales convolucionales (CNN): CNN construida desde cero, AlexNet, CNN con técnica de aumento de datos, FE-VGG16, FE-ResNet50 y FT-VGG16. Estos modelos fueron evaluados mediante un conjunto de métricas derivadas de la matriz de confusión, la curva ROC (característica operativa del receptor) de cada modelo y el valor correspondiente al área bajo la curva (AUC). El mejor desempeño correspondió al modelo FT-VGG16 que fusiona el modelo preentrenado VGG-16 con un bloque de capas completamente conectadas. Finalmente, se reportan resultados satisfactorios que permiten concluir que la aplicación de modelos de Transfer Learning para la clasificación de imágenes de pie diabético constituye una herramienta viable para el diagnóstico no invasivo de T2D.

Transferencia de Aprendizaje, Clasificación, Diagnóstico

Citation: CUTIÉ-TORRES, Carmen, LUNA-ROSAS, Francisco Javier, LUNA-MEDINA, Marisol and DUNAY-ACEVEDO, Cesar. Transfer Learning to improve the Diagnosis of Type 2 Diabetes Mellitus (T2D). Journal-Democratic Republic of Congo. 2023, 9-16: 9-21

* Correspondence to Author (e-mail: ccutietorres@gmail.com)
† Researcher contributing first author.

1. Introduction

Diabetes mellitus is currently a chronic disease with high incidence rates worldwide. There are several types of diabetes, including type 2 diabetes (T2D) which is closely related to the body's response or resistance to the hormone insulin and endocrine pancreatic beta cell dysfunction (WHO Library Cataloging-in-Publication Data, n.d.).

T2D has a prevalence of 10.3% in Mexico according to the 2021 National Health and Nutrition Survey (ESNAUT), which indicated that more than 12 million people over the age of 20 live with this disease. The country's death rate was 11.0 per 10,000 inhabitants, of which 74.9% corresponded to T2D and only 48% were affiliated with a Health Institution (INEGI, 2022).

Several complications associated with T2D include cardiovascular diseases, neuropathy, nephropathy, diabetic retinopathy, ulcerations and frequent infections.

Diabetic foot ulcer has become a condition that affects the quality of life of patients with T2D due to the high numbers of amputations and mortality that it entails. According to the reports of the Hospital Type 2 Diabetes Mellitus Epidemiological Surveillance System for 2022, the diabetic foot is recognized as one of the most frequent causes of admission (12.5% of total admissions), which includes patients who did not know they were sick previously (Salud, n.d.).

The American Diabetes Association (ADA) recognizes glycosylated hemoglobin (A1C), fasting plasma glucose (FPG), the Oral Glucose Tolerance Test (OGTT) and the Random plasma glucose test as clinical methods for manual diagnosis of diabetes. These are tests performed by venous puncture, in health centers or outpatient units with the presence of personnel specialized in the manipulation of blood fluids (American Diabetes Association, n.d.).

Other devices for daily use are the traditional glucometer or the Continuous Glucose Monitoring (CGM) systems. These methods require venous or intramuscular puncture, causing frequent discomfort and infections to the patient (Patel & Priefer, 2021).

Nevertheless, despite its existence, between 30% and 80% of D2T cases are not detected promptly due to the slow progression of the disease symptoms (OMS, n.d.).

Scientific community has adopted different approaches to improve the detection and early diagnosis of T2D, including non-invasive methods, the use of advanced technologies, awareness, and education about the disease. These efforts are aimed at reducing the lethal consequences of T2D and improving the quality of life for those affected.

In this regard, they highlight the use of Artificial Intelligence (AI) algorithms in tasks of classifying medical images or data from patient medical records. Numerous models based on Machine Learning and Deep Learning techniques make it possible to diagnose T2D with precision, sensitivity, and specificity criteria like those perceived by medical specialists. They also allow large data sets to be analyzed quickly and accurately, which can help identify disease-related patterns and correlations (Afsaneh *et al.*, 2022; Fregoso-Aparicio *et al*., 2021; Silva *et al*., 2021).

The goal of this research is to develop a computational model based on Transfer Learning techniques for non-invasive diagnosis of T2D using images of diabetic feet from both healthy and diseased patients.

The proposed approach seeks to provide an effective and reliable solution in the early detection of T2D, which could allow timely treatment and improve the quality of life of patients.

Our paper is structured as follows: in Section 2 concepts of interest are introduced, as well as a brief state of the art related to the non-invasive diagnosis of T2D. Section 3 presents the methodology used which is divided into 3 phases with 5 fundamental steps or activities. In Section 4 we discuss the results, while in Section 5 we acknowledge the contributions received. In Section 6 we determine the conclusions and contributions of our work. In Section 7 we show the references bibliography used through the investigation.

2. Related Works

Machine Learning (ML) is a subset or discipline of the AI field made up of algorithms that learn automatically and identify patterns in the data. This data is supplied to them during their training stage. Notwithstanding, ML algorithms do not need to be programmed with specific rules and can be applied to both classification and regression tasks. They are divided into 3 categories: Supervised Learning, Unsupervised Learning, and Reinforcement Learning.

Deep Learning (DL) is considered a subset of ML, since they are nourished by the basic principles of Artificial Neural Networks (ANN) inspired by the interconnection and functioning of neurons in the human brain. Like these, deep learning networks are composed of layers of neurons that learn progressively, using algorithms such as backpropagation during the training process. The difference between ANNs and DL consists in the depth or number of stacked layers (more than three layers) that make up a DL model, which provide greater complexity and the ability to discover patterns in large data collections.

To carry out the non-invasive diagnosis of T2D using Machine Learning, Carter *et al*. (2019) used Random Forests to classify diabetic nails, Zhang *et al*. (2021) developed models with Boosting and Bagging techniques to deal with unbalanced data from diabetic patients, Agrawal *et al*. (2022) applied Logistic Regression algorithms, k nearest neighbors, Decision Trees, Support Vector Machines in D2T classification tasks with a dataset obtained using the iGLU 2.0 serum glucometer (Jain *et al*., 2020). Also, Sanchez-Brito *et al*. (2022) use Artificial Neural Networks to classify the disease using patient saliva spectra obtained using Attenuated Total Reflectance -Fourier Transform InfraRed (ATR-FTIR) spectroscopy technique.

Within Deep Learning, publications highlight the growing interest in the use of Convolutional Neural Networks (CNN) given its ability to detect patterns in medical images. The high sensitivity of these models, as well as their specificity when discriminating between different classes, makes them potential diagnostic tools.

Qiao *et al*. (2020) classified different stages of diabetic retinopathy (early, moderate, and severe non-proliferative diabetic retinopathy) using fundus images. Semantic segmentation algorithm capable of distinguishing between an infected and normal retina was implemented to detect early signs such as microaneurysms or macular edema.

Tang *et al*. (2020) developed a CNN-based framework and fuzzy-c means algorithm models to predict the onset of type 2 diabetes one year in advance using quantitative patient information and abdominal computed tomography images.

Cruz-Vega *et al*. (2020) implemented AlexNet and GoogleNet pretrained models based on Transfer Learning and in turn proposed a new structure trained from scratch with plantar thermography images of diabetic patients.

Munadi *et al*. (2022) also delved into the use of thermal imaging and reported a model based on MobileNetV2 and ShuffleNet. The binary classification resulting from both models was merged or combined using the Fusion Decision technique (Wang *et al*., 2017).

Solutions such as DFUNet (Goyal *et al*., 2020), DFU_QUTNet (Alzubaidi *et al*., 2020), YOLOv5, Faster R–CNN, EfficientDet (Yap *et al*., 2021) and CKB-DeiT-B-D (Xu *et al*., 2022) also made contributions in the classification of images of diseased epidermal tissue or ulcerations.

3. Methodology

We propose a methodology consisting of 3 fundamental Phases: Analysis and Design, Development and Evaluation. These phases contemplate a group of steps or activities that allow the objective of the investigation to be fulfilled:

– Analysis and Design Phases: Firstly, a search and acquisition of the dataset that best fits our object of study is carried out. Afterwards, the different Deep Learning models that will intervene in the training and validation stages are designed.

- Development Phase: The steps of this phase include the execution of the training of each model designed in the previous stage.

- Evaluation Phase: Finally, the models are validated through a group of performance metrics equivalent to those used in clinical trials.

3.1 Dataset acquisition

The Diabetic Foot Ulcer (DFU) dataset used in this research was obtained from the Kaggle.com website (*Diabetic Foot Ulcer (DFU)*, n.d.). According to the authors Alzubaidi *et al*. (2022) the dataset was generated at the Al-Nasiriyah Center for Endocrinology and Diabetics in Iraq and is composed of patches of damaged or healthy skin. These patches were obtained by detecting and segmenting Regions of Interest (ROI) that were labeled by medical experts according to their respective classes.

The dataset contains a total of 1055 images with dimensions of 224 x 224, which were classified into Abnormal (ulcerated skin) and Normal (healthy skin), with 512 and 543 files respectively.

3.2 Model Design

Brief Explanation of Convolutional Neural Networks (CNN)

The CNN is a type of deep neural network made up of several hidden layers used in the field of machine vision and object recognition due to its ability to try to mimic the human visual cortex.

As same as Artificial Neural Networks, it uses the backpropagation algorithm in its learning, with a hierarchical structure that allows its layers to extract patterns in the data from low (lines, curves, contours, etc.) to high level (complex shapes, objects, faces, etc.), based on the order in which they are stacked.

The main elements of CNNs are:

- Convolution layers: Hidden layers in which multiplicative operations are executed between the matrix made up of the RGB channels of the input image in a range of 0 to 255 pixels, and the kernel, also known as a filter, convolution matrix, or synaptic weight matrix. These are responsible for activating different characteristics of the image. As Figure 1 indicates, the convolution is performed iteratively calculating the dot product between portions of the input matrix and the kernel. This operation moves until all the elements of the feature map, also known as 3D tensor, are covered.

Mathematically it can be stated with the following equation:

$$f \circledast h = g \quad (1),$$

where f and h correspond to different functions, and g is the output or feature map.

In a convolutional layer, the kernel and the bias are considered trainable parameters that are optimized by algorithms based on gradient descent. This technique uses the calculation of the partial derivative of the loss function with respect to the different parameters mentioned above.

- Pooling Layers: They are used to reduce the dimension of the matrices resulting from the convolution by subsampling the input, which allows preserving its most representative characteristics. There are several ways to condense these matrices, for example: Max-pooling that calculates the maximum value of a portion of the total elements, and Average-Pooling that calculates the mean. The stride parameter specifies the step or jump of the displacement of the pooling window in the array.

- Flatten Layers: Converts the 3D tensor to a 1D or vector to serve as input to a group of fully connected layers.

– Activation function: It is located at the output of each neuron and constitutes the threshold or limiting function that modifies its result, in such a way that it can continue with the propagation of its value towards another neuron. There are several types: step, sigmoidal, rectifying (ReLU), hyperbolic tangent, softmax, among others.

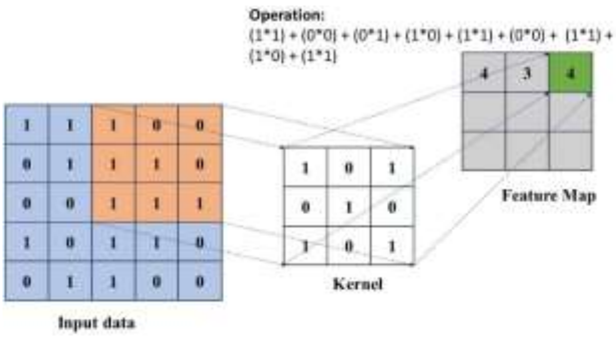


Figure 1. Convolution operation.
Source: Own Elaboration

Simple CNN

The architecture of the simple or built from scratch CNN model consisted of 2 convolutional (2D) layers followed by a MaxPooling layer to reduce the dimensions of the extracted feature maps. In each case the activation function was ReLU. The features that were obtained from the convolution step were flattened using a Flatten layer.

Classification task was performed using two fully connected layer and an output layer, with 50 and 1 neuron respectively. The activation functions were ReLU and sigmoid for classification, as shown in Table 1.

Layer	Kernel size / Filter	Activation function
Conv2D	3 x 3 x 32	ReLU
MaxPool2D		
Conv2D	3 x 3 x 64	ReLU
MaxPool2D	-	-
Flatten	-	-
Dense	50	ReLU
Dense	50	ReLU
Dense	1	sigmoid

Table 1. Simple CNN Architecture
Source: Own Elaboration

Based on AlexNet

In this section we present a model based on the AlexNet network architecture, developed by Krizhevsky *et al*. (2012). AlexNet includes more complex elements compared to the simple CNN, such as Dropout regularization layers used to reduce overfitting of the data by turning off neurons with little significance to the model.

The original model is composed of 5 convolutional layers (Conv2D) with ReLU type activation functions. The first, second and fifth layers followed by 3 pooling layers that seek to condense the information from the previous layer or reduce its dimensionality.

Our proposed model adds Batch Normalization layers after each reduction layer, since it allows to reduce internal covariate changes between minibatches (Ioffe & Szegedy, 2015).

The first layer is composed of filters with dimensions of 11x11, the second with 5x5, and 3x3 in the rest of the convolution layers. Details related to this architecture are shown in Table 2.

We used the Python library called OpenCV to adapt the dataset to the dimensions required by the neural network. In this way, all the images in the dataset were resized to have a size of 227x227 pixels, allowing them to be compatible with the input of the neural network.

Layer	Kernel size / Filter	Activation function
Conv2D	11 x11 x 96	ReLU
BatchNormalization	-	-
MaxPool2D	-	-
Conv2D	5 x 5 x 256	ReLU
BatchNormalization	-	-
MaxPool2D	-	-
Conv2D	3 x 3 x 384	ReLU
BatchNormalization	-	-
Conv2D	3 x 3 x 384	ReLU
BatchNormalization	-	-
Conv2D	3 x 3 x 256	ReLU
BatchNormalization	-	-
MaxPool2D	-	-
Flatten	-	-
Dense	4096	ReLU
Dropout (0.5)		
Dense	4096	ReLU
Dropout (0.5)	-	-
Dense	1	Sigmoid

Table 2. AlexNet Architecture
Source: Own Elaboration

Data Augmentation

One of the fundamental problems when analyzing medical images with Deep Learning is the lack of high-quality labeled data. In the medical field, the acquisition of medical data, such as magnetic resonance imaging (MRI), computed tomography (CT), or x-rays, often involves significant costs and resources.

Medical images are often highly varied and contain detailed and complex information. This makes the task of training Deep Learning models even more difficult, as a large amount of diversified and representative data would be needed to capture the variability of medical images and ensure that the model can generalize correctly.

Data augmentation is a technique used to increase the amount and diversity of training data available. It consists of applying random transformations to the existing data to create new samples, which helps improve the performance and generalization of the model to new instances.

In this context, it is useful since we have a limited set of images for a classification problem (1055 elements), which can lead to overfitting problems.

For these purposes, we implemented the ImageDatagenerator class through Keras library, in charge of generating batches of images indefinitely, as shown in Figure 2.

The transformations applied to our dataset of diabetic foot images are detailed below:

- Rotation_range: Rotation of images with respect to the angle denoted in degrees (0-360 degrees).
- Width_shift_range: Random horizontal shift.
- height_shift_range: Random vertical shift.
- Shear_range: Cropping of the image along an axis creating new angles of perception.
- Zoom_range: Increase on the image both horizontally and vertically.
- Horizontal_flip: Flip the image horizontally.
- Fill_mode: Filling of empty pixels with the value of the closest pixels.

Finally, we applied this technique to the training dataset and developed the model using the Simple CNN model architecture described in previous sections.

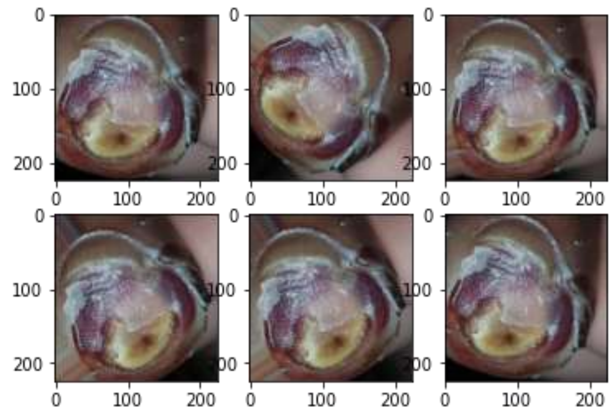


Figure 2 Rotation of an image at an angle of 45 degrees.
Source: Own Elaboration

Transfer Learning

Transfer learning is a technique that allows taking advantage of the knowledge acquired by a model trained in a broad task to be used in a more specific one with a more limited data set. In the present investigation, pretrained models were used in the Imagenet database since it contains more than 14 million annotated images and is designed to be used in visual recognition tasks.

The advantage of this approach is that the pretrained models have already learned to extract relevant features from the images, such as edges, textures, or objects. Taking advantage of this knowledge and adjusting it to the specific task of medical image classification provides higher performance with less data. Therefore, computational costs are reduced by accelerating the training stage of the model since it has optimized weights, thereby reducing the number of parameters to train.

We propose an architecture with a separation of tasks into two blocks as shown in Figure 3. This allows a modular approach in model training. The first part, which includes the convolution and pooling layers, is kept fixed or "frozen", which means that its weight matrices are not updated during training.

On the other hand, the second block that contains the fully connected layers is trained with the data from the diabetic foot image dataset. It is here where the essential modifications of the network occur by updating its most important parameters. This step allows the model to specialize in the task of classifying the two classes of foot patches: abnormal and normal.

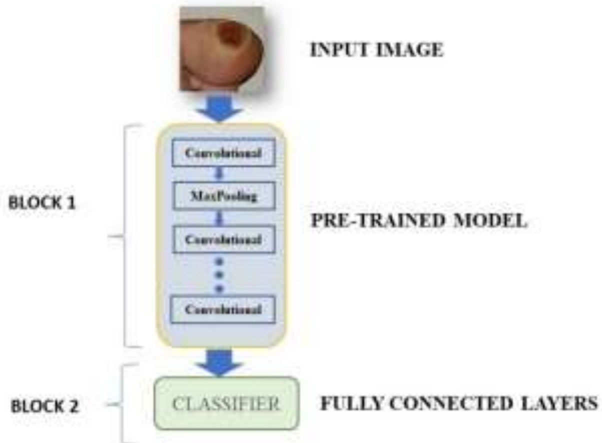


Figure 3. Transfer Learning Approach
Source: Own Elaboration

Feature Extraction

In this section, the VGG16 and ResNet50 pretrained models were developed for the extraction of relevant features according to the modular approach of Transfer Learning discussed in the previous section.

According to the scientific literature (Hacisoftaoglu *et al.*, 2020; Hossain *et al.*, 2022; Jiang *et al.*, 2021; Kathamuthu *et al.*, 2023; Shukla & Tiwari, 2022) these models achieve good results in the classification of medical images, are easy to implement and consume fewer physical resources compared to other deeper networks.

The VGG-16 architecture consists of 2 blocks of 2 2D convolutional layers and 3 blocks of 3 2D convolutional layers with filters of size 3 X 3. Each block is followed by a MaxPooling2D layer.

Similarly, the ResNet50 model, which is a variant of the 50-layer CNN, incorporates the use of residual connections which help mitigate the Vanishing gradient problem. Its architecture is defined by identity blocks and convolutional blocks with 1x1, 3x3 and 1x1 filters.

In both cases, the classification task is performed by a set of fully connected layers with two Dense layers of 50 neurons with ReLU activation function and an output layer with a single neuron with sigmoid activation function.

Fine Tuning

A transfer learning technique called fine tuning is used to modify a pretrained model by training some or all its layers with more task-specific data. For this case, we used the architecture used in the previous feature extraction model with VGG-16.

We divided the training into two fundamental stages: freezing the first layers of the model considered low-level due to their ability to extract generic features, and retraining the higher-level layers that are responsible for extracting more specific patterns. In this second stage, the weights of the unfreezed layers do change.

To obtain the proposed model, convolution block number 5 (block5_conv1) was unfrozen within the VGG-16 pretrained model. This block allows training a total of 7,079,424 parameters.

3.3 Model Training

The implementation of the solutions was carried out using the Keras and TensorFlow frameworks. We used Anaconda development environment with Python programming language.

The models were trained for 50 epochs with 75% of the data set. For validation, 15% of the total was used and the remaining 10% was reserved for the prediction of new entries. The optimizer used in all cases was RMSProp with a learning rate of 0.000001. Considering that we are dealing with a two-class classification problem: sick and healthy, we selected binary_crossentropy loss function.

Also, Mini-Batch Gradient Descent was selected as the learning algorithm. Therefore, the Batch Size of the model is equivalent to 20 batches, which indicates the number of samples that will be analyzed before updating the error value, the weight and bias matrix.

This technique helps to optimize internal memory consumption when working with limited computational resources. It also allows parallelizing the gradient computation by splitting mini batches across multiple cores or processing devices, which can be especially useful on systems with multiple processing units, such as GPUs.

3.4 Model Validation

To evaluate the ability of the models to correctly classify diabetic and healthy patients, a set of metrics based on the Confusion Matrix were calculated as shown in Table 3. The ROC curve is also used to demonstrate the performance of each model for testing data set.

The 4 cells of the Matrix refer to: True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN) cases.

		Prediction	
		Positive	Negative
Real	Positive	TP	FN
	Negative	FP	TN

Table 3. Classification results in positive and negative classes.
Source: Vanacore et al. (2022)

Formulas for calculating each metric are defined below:

Accuracy:

$$Acc = (TN + TP)/(TN + FP + FN + TP) \quad (2)$$

Positive Precision o Sensitivity (PP):

$$PP = (TP)/(FN + TP) \quad (3)$$

Negative Precision o Specificity (PN):

$$NP = (TN)/(FP + TN) \quad (4)$$

False positives (PFP):

$$PFP = (FP)/(FP + TN) \quad (5)$$

False negatives (PFN):

$$PFN = (FN)/(FN + TP) \quad (6)$$

Positive Assertiveness (PA):

$$PA = (TP)/(FP + TP) \quad (7)$$

Negative Assertiveness (NA):

$$NA = (TN)/(FN + TN) \quad (8)$$

3.5 Comparative analysis of models

In this last step of the methodology, the results obtained for the 6 Deep Learning models that were coded are compared. We implemented a number of 7 metrics derived from the Confusion Matrix, the loss function value, and the AUC value. The graphs of the loss function and the ROC curve were also analyzed. The results are shown in Table 4 and Table 5. They are discussed in the next section.

4. Results and discussion

In this work, 6 CNN models were developed for the classification of type 2 diabetes by analyzing images of the diabetic foot. To this end, the Keras and Tensorflow development frameworks were used.

Models were trained and tested over 50 epochs, and data augmentation techniques were employed during training to avoid overfitting and improve exposure to diverse features. To partition the dataset and evaluate the performance of the models, we used the train-test Split technique with 75% of the data for training, 15% for validation, and 10% reserved for predictions. The results obtained are shown in Table 4 and 5.

All models used the Data Augmentation technique applied only to train dataset, but Simple CNN model, which was exposed to 797 images of healthy and diseased feet during its training and to 200 images during validation.

Model	Acc	Loss	PP	NP	PFP
Simple CNN	95.49	0.035	100	92.71	7.29
AlexNet	96.49	0.045	95.19	95.83	4.17
DA	97	0.03	96.15	97.92	2.08
FE-VGG16	99	0.01	100	97.92	2.08
FE-ResNet50	98	0.02	100	95.83	4.17
FT-VGG16	99.50	0.005	100	98.96	1.04

Table 4 Performance metrics results for each model (Part 1)
Source: Own Elaboration

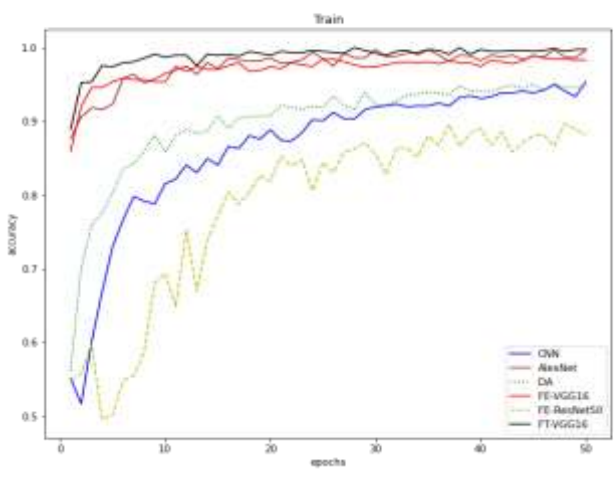
ISSN 2414-4924

Model	PFN	PA	NA
Simple CNN	0	93.69	100
AlexNet	4.81	96.12	94.85
DA	3.85	98.04	95.92
FE-VGG16	0	98.11	100
FE-ResNet50	0	96.30	100
FT-VGG16	0	99.05	100

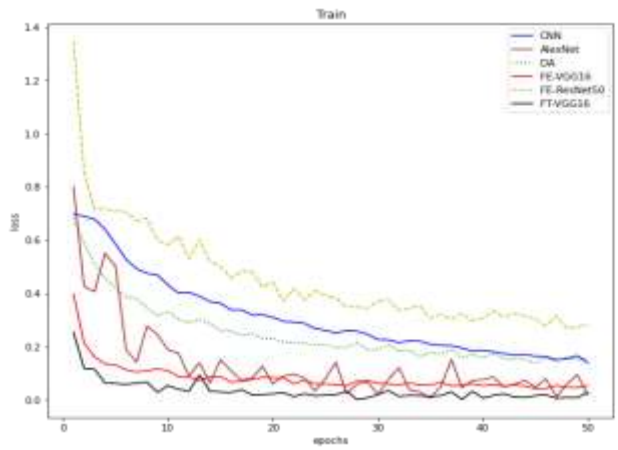
Table 5 Performance metrics results for each model (Part 2)
Source: Own elaboration

As we saw in reported values, all models exhibit results above 95%. Similarly, Graphic 1 shows Accuracy values plotted in function of the training epochs. The FE-VGG16, FT-VGG16 and AlexNet models achieved the best results in their training phase.

Since first epochs the Accuracy values are above 85%, which indicates that models capture a greater number of characteristics in early periods of training. On the other hand, no signs of overfitting were observed for these models since their trend is upward in the case of Accuracy. When analyzing the behavior of the loss function showed in Graphic 2, a downward tendency can be seen in its values, which are in ranges of less than 4%.



Graphic 1. Accuracy graphs of the models. CCN: Simple Convolutional Neural Network, DA: Data augmentation, FE-VGG16: Feature extraction with VGG-16 pretrained model, FE-ResNet50: Feature extraction with ResNet50 pretrained model, FT: Fine tuning with VGG-16 pretrained model
Source: Own Elaboration



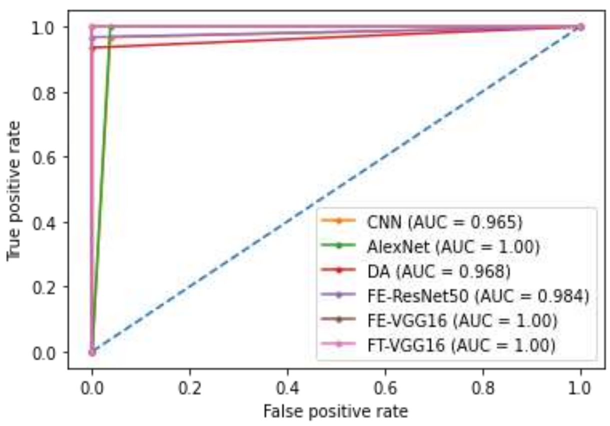
Graphic 2. Loss graphs of the models. CCN: Simple Convolutional Neural Network, DA: Data augmentation, FE-VGG16: Feature extraction with VGG-16 pretrained model, FE-ResNet50: Feature extraction with ResNet50 pretrained model, FT: Fine tuning with VGG-16 pretrained model.
Source: Own Elaboration

Graphic 3 shows the ROC curve of all models. This graph is important to analyze the behavior of the Sensitivity and Specificity values of the models, as well as their diagnostic capacity. It is used in clinical trials since it allows evaluating the ability of the proposed methods to correctly differentiate classes (Martínez Pérez & Pérez Martin, 2023). The results of the metric called AUC, which shows in numerical values the benefits of each model compared to the non-discrimination line with a value of 0.50, were also analyzed.

Accuracy, Sensitivity, Specificity values and others reported in Table 4, made possible to conclude that the best performances are obtained by models that implement Transfer Learning techniques such as feature extraction and fine tuning. In this regard, those that use the pretrained model VGG-16 stand out over the rest.

AlexNet model also reports good results even though its Accuracy value is similar to model with Data Augmentation techniques. Nertheless, AUC value is 100% in the first case. We assumed that this is due to the depth of the model evidenced in the number of hidden layers and activation neurons.

Also, to the use of regularization layers such as Batch Normalization and Dropout that help to avoid overtraining the model.



Graphic 3 Area under the curve per models
Source: Own Elaboration

Finally, Figure 6 shows the predictions obtained using the FT-VGG16 model. The prediction process occurs by exposing the trained model to new data to check if it has really learned to detect relevant patterns in the images. In this case, a total of 58 images are processed (27 corresponding diseased skin patches and 31 healthy ones) that were not used in the previous training and validation phases. All were correctly classified, which validates the results of the metrics mentioned above.

5. Acknowledgement

We thank the Technological Institute of Aguascalientes (ITA) and the National Council of Science and Technology (CONAHCYT) for their support in this research.

6. Conclusions

At present day, a continuous rise is projected in the cases diagnosed with T2D. In proportion to these statistics, an increase in the health complications is expected.

The early diagnosis of this disease and the incorporation of healthier lifestyles in people constitute key elements to avoid the high prevalence rates of this deadly condition.

Figure 6 Generation of new predictions for the two classes of skin patches (Model FT-VGG16).
Source: Own Elaboration

Improving the quality of life of patients is also an objective for the scientific community. Less invasive diagnostic variants have been explored that contribute to saving costs. They are efficient and guarantee timely diagnosis using Information Technology (IT) and electronic devices related to the Internet of Things (IoT) paradigm.

Consequently, the present work implements a group of Deep Learning models to classify T2D using diabetic foot images. It is important to consider that in Mexico diabetic foot is one of the most frequent causes of admission in patients without a previous diagnosis.

As a final solution, the FT-VGG16 model is proposed, which merges data augmentation and Transfer Learning techniques. They include the use of the VGG-16 pretrained model for the extraction of relevant features from the set of input images and the fine adjustment with the purpose of further specialize the final layers of the pretrained model, since they are the ones that detect the highest level features in the network. The proposed model presented a very favorable performance, standing out for a global precision of 99.5%, sensitivity of 100%, specificity of 98.96% and AUC of 100%.

With this research we hope to contribute to the knowledge generation in medical image classification´s field, especially those related to T2D. Performance evaluation of models based on metrics consistent with the work carried out by health professionals provides a theoretical and practical framework. It validates the application of Transfer Learning techniques within the decision making and disease diagnosis process.

7. References

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