

#### Volume: 07 Issue: 10 | October - 2023

SJIF Rating: 8.176

# MONITORING AND ANALYZING DIABETIC FOOT ULCER USING **RESNET50 IN DEEP LEARNING**

DIVYA.G ., PG STUDENT Dept. Of Computer Science And Engineering, Sri Krishna College Of Engineering And Technology, Coimbatore, Tamilnadu,India. srikrishnacollegetensorflow@gmail.com

Dr.VIJAYA., PROFESSOR Dept.Of Computer Science And Engineering, Sri Krishna College Of Engineering And Technology, Coimbatore, Tamilnadu,India. vijayag@skcet.ac.in

#### Abstract

This paper introduces a deep learning approach using the ResNet50 algorithm within Google Colab to detect diabetic foot ulcers. Early identification of these ulcers is crucial to prevent leg amputations. Leveraging a diverse dataset, the model exhibits high accuracy and sensitivity, offering a cost-effective solution for timely intervention in diabetic foot ulcers, there by improving patient outcomes.

## I) INTRODUCTION

Diabetic foot ulcers are a pervasive and serious complication among individuals with diabetes, often culminating in lower limb amputations. The timely identification of these ulcers is imperative to prevent such life-altering outcomes. This paper introduces a novel approach utilizing deep learning and the ResNet50 algorithm within the Google Colab environment to detect diabetic foot ulcers. Our research focuses on enhancing patient outcomes by enabling early intervention and treatment, thereby mitigating the need for amputations in diabetic patients.

# **II) PROPOSED SYSTEM**

#### **Proposed Methodology**

The proposed method uses deep convolutional neural network models that includes different stages like the preprocessing augmentation, training the models applying different DL models & validation, and prediction

L



## Augmentation of training patch

To function effectively, CNN needs a lot of labeled training data Furthermore, collecting a lot of medical data is expensive and challenging. To Get better performance and prevent overfitting, we used data augmentation approaches. In data augmentation, we used a variety of image processing techniques, including rotation, flipping, employing multiple color models, contrast improvement, and random scaling to create the desired effect.

#### **Classification Models**

Deep learning is the key technology behind a lot of high-end advancements like driverless cars, voice control in gadgets like tablets, smartphones, hands-free speakers, sensors, etc., and many more. The issue dealing with the current models is that the depth, width, and resolution are interdependent, and their values fluctuate depending on the available resources. ConvNets are difficult to scale, hence most traditional methods scale them in one of these dimensions. It is observed that all the models use Rectified Linear Unit (ReLU) as the activation function. The ReLU activation function is a Straight for- ward calculation that gives an immediate response of the value entered or 0.0 if the input is 0.0 or less.

Train the modified ResNet-50 model on your labeled dataset. Use a suitable loss function, like categorical crossentropy, to optimize the model's parameters. Monitor the training process with validation data to prevent overfitting. You can also consider techniques like early stopping to prevent training from continuing when validation performance starts to degrade. After training, evaluate the model's performance on a separate test dataset that it hasn't seen during training. Use metrics like accuracy, precision, recall, and F1-score to assess its performance.

## **Fine-Tuning and Optimization:**

Depending on the performance, you might consider fine-tuning the model by adjusting hyperparameters, modifying the architecture, experimenting with different optimizers.

#### **Deployment and Real-Time Inference:**

Once you have a trained model, optimize it for deployment on mobile devices or in real-time scenarios. Techniques like quantization and model compression can help reduce model size and improve inference speed. Remember that while ResNet-50 is a powerful architecture, success depends on having a diverse and representative dataset, thoughtful preprocessing, and effective fine-tuning. Additionally, explain ability and interpretability are important considerations, especially in medical applications, so it's valuable to visualize and understand how the model is making its decisions.



co f	inalproje	ct resnet50.ipynb - (	Cola 🗙	ၸ diabetes	project - Colaboratory	× 🚥 pl	ot using se	aborn - I	Colaborato	- ×   +						$\sim$	-	J ×
<del>~</del>	→ C	Colab.res	earch.goo	ogle.com/dri	ve/1i-8n-40VyJUmP	t2159xB81qd2	dhwJa8H	I								Ge	☆ □	: 🚯
=	+ Coo	de + Text													Co	nnect 👻	- a q	r 🗸 🗸
۹	0	import numpy import panda	as np sas pd												↑ ↓	© <b>E</b>	\$	
{x}	0	#loading dia diabetes_dat	betics aset=pd	dataset to .read_csv(	dataframe "/content/diabet	es.csv")												
	[]	pd.read_csv?																
	[]	<pre># printing t diabetes_dat</pre>	he firs aset.he	t 5 rows o ad()	f the dataset													
		Pregnanci	ies Glu	cose Bloo	odPressure SkinT	hickness ]	Insulin	BMI	Diabete	sPedigreeFu	nction	Age	Outcome					
		0	6	148	72	35	0	33.6			0.627	50	1					
		1	1	85	66	29	0	26.6			0.351	31	0					
		2	8	183	64	0	0	23.3			0.672	32	1					
		3	1	89	66	23	94	28.1			0.167	21	0					
		4	0	137	40	35	168	43.1			2.288	33	1					
$\langle \rangle$	[]	diabetes_dat	aset.sh	ape														
)-		(768, 9)																
								_					_	-			C-00 A	• >
Ŧ	РT	ype here to sear	rch	(SS)	H 💽 I	<b>i</b>		0	0	💴 🧿	Ŵ			📥 26°C	^ ĝ	🚱 🗆 ¢	()) 6:09 A ()) 10/2/20	123 🐴

The above chart shows the Diabetic Dataset to display its head which shows the few rows of dataset it includes columns like patient information and health metrics such as BMI,Blood pressure,Age,Pregancies,Insulin and Outcomes.

## FIGURE 2

œ	finalproje	iett resnet50.ipynb - Coli: 🗙 🚾 diabetes project - Colaboratory 🗙 😋 plot using seaborn - Colaborator 🗙 🕇 🕇	~	-	٥	×
←	→ C	C in colab.research.google.com/drive/1i-8n-40Vy/UmPt2l59x881qd2dhwJa8H#scrollTo=10dYzbZgQOrJ	GĖ	☆	ه ا	:
:=	+ Co	ode + Text C	onnect 🖣	-	<b>¢</b>	~
۹	0	<pre># locating a particular column print(diabetes_df.iloc[:,0]) # first column</pre>	↓ @ E	•		:
{x}	Ð	<pre> 0 6 1 1 1 2 8 3 1 4 0 763 10 764 2 765 5 766 1 767 1 Name: Pregnancles, Length: 768, dtype: int64</pre>				
<>	[]	<pre>print(diabetes_df.iloc[:,1]) # second column</pre>				
	٦ كر	Type here to search 🥳 🛱 💽 🚍 🛱 🕋 🍥 🔍 💷 💿 🧟 🧾 🕵 🔺 📤 26°C 🗛	ê 🖪 📼	43) 6:11 10/2,	AM 2023	×

The chart shows the location of rows and column of particular field of diabetic patient history



co fi	nalproje	ct resnet50.ipynt	b - Cola 🗙	co diabetes p	roject - (	Colaboratory	× 🚥 pl	ot using seab	orn - Col	aborator; ×   +						~	- 6	) >	<
<del>(</del>	→ C	🗎 colab.r	research.go	ogle.com/driv	e/1i-8n	-40VyJUmPt2I	159xB81qd2	dhwJa8H#	crollTo	=Wc4199gehGej					C	e e	☆□		:
:=	+ Coo	de + Text													Con	nect 👻	# Ø	~	
Q	0	diabetes_d	f.tail												$\uparrow \downarrow$	0 <b>Q</b>	¢ 😡 1	1 E	
	⋳	<bound met<="" th=""><th>hod NDFra</th><th>me.tail of</th><th>Р</th><th>regnancies</th><th>Glucose</th><th>BloodPre</th><th>ssure</th><th>SkinThickness</th><th>Insulin</th><th>BMI \</th><th></th><th></th><th></th><th></th><th></th><th></th><th>1</th></bound>	hod NDFra	me.tail of	Р	regnancies	Glucose	BloodPre	ssure	SkinThickness	Insulin	BMI \							1
$\{x\}$		0	6	148		72	35	0	33.6										
		1	1	85		66	29	6	26.6										
		2	1	80		66	23	94	25.5										
		4		137		40	35	168	43.1										
		763	10	101		76	48	180	32.9										
		764	2	122		70	27	0	36.8										
		765	5	121		72	23	112	26.2										
		766	1	126		60	0	0	30.1										
		767	1	93		70	31	0	30.4										
		Diabe	tesPedigr	eeFunction	Age	Outcome													
		0		0.627	50	1													
		1		0.351	31	0													
		2		0.672	32	1													
		3		0.167	21	0													
		4		2.288	33	1													
		763		0.171	63														
		764		0.340	27	ē													
		765		0.245	30	0													
		766		0.349	47	1													
		767		0.315	23	0													
<>		[768 rows	x 9 colum	ins]>															
		-		-															el.
>_	[]	#https://m	atplotlib	.org/stable	/plot_	types/array	/s/index.	tml											
		#conda ins	tall -c c	onda-forge	matnlo	tlib													
				<b>AND</b>			_	<u> </u>	_	-		-	Contraction of the local division of the loc				6:11 AM		Ŷ
	РT	ype here to s	earch	(See)	⊒i	C 🖡			? (	) 💷 🧕	0	u 🐼		🦰 26°C	∧ ĝ	🔁 🗆 <	<sup>(3)</sup> 10/2/202	23 🤞	

The above chart shows the tail of diabetic dataset which includes Pregnancies, Glucose Blood Pressure, Skin, Thickness, Insulin, BMI, Diabetes, Pedigree Function, Age and Outcome

#### FIGURE 4



The above chart shows the Diabetic dataset using Seaborn function for using bar chart in calculating Outcome and count for Diabetic dataset taken from kaggle .





The above chart shows the metrics like Pregancies and count are calculated using seaborn function in mat plot libraries.

## FIGURE 6

Code	e + Text
D	
-	)
	# Load the Training and Validation Dataset
	<pre>train_ds = datagen.flow_from_directory(</pre>
	TRAIN_PATH,
	target_size=(224,224),
	parcn_size=04,
	cubs_mode= categorical,
	souser ( samang ,
	train labels = train ds.classes
	val_ds = datagen.flow_from_directory(
	TRAIN_PATH,
	target_size=(224,224),
	batch_size=64,
	class_mode- categorical',
	subset='validation',
	Seeaw
	x
	val labale = val de classas
	ANTTRACTA - ANTTALCASTON
Ð	Found 845 images belonging to 2 classes.

The above image shows the training and validation categorical of dataset using tensorflow for coding it show how many images belongs to which classes.

Т





The above figure shows the class names of diabetic foot ulcer in which they are dealing with two types of classes Abnormal (Ulcer) and Normal ulcer (Healthy skin).

## FIGURE 8



The above figure show Visualize the training dataset by using following tensorflow

Plt.figure(figsize=(7, 7))
for images, labels in train\_ds:
for i in range(9):
ax = plt.subplot(3, 3, i + 1)
plt.imshow(images[i])
plt.title(class\_names[labels[i].argmax()])
plt.axis('off')
break # Only show the first batch of images
plt.tight\_layout()
plt.show()

Ι





The figure shows the Visualize the testing dataset of Diabetic foot ulcer

plt.figure(figsize = (7, 7))

i = 0;

for images in test\_ds.take(6):

ax = plt.subplot(3, 3, i + 1)

plt.imshow(images.numpy().astype("uint8"))

plt.axis("off")

I += 1

FIGURE 10

+ Cod	+ Text All changes saved			Connect aru 👻 🚉 🐯
0	history=model1.fit(train_ds	s, callbacks=[lr_callback	<pre>stop_callback],batch_size=32, epochs=30, validation_data=val_ds)</pre>	↑ ↓ ∞ <b>티 ☆ ြ i</b>
⊡	Epoch 1/30			
	Epoch 2/30	versioned - 1982 asystet	- Ioss: 0.8486 - accuracy: 0.4982 - Val_Ioss: 0.7500 - Val_accuracy: 0.48	857 - IP: 0.0010
	14/14 [	] - 4s 282ms/str	) - loss: 0.6943 - accuracy: 0.4994 - val loss: 0.6528 - val accuracy: 0.4	4857 - lr: 0.0010
	Epoch 3/30			
	14/14 [	] - 5s 329ms/ste	- loss: 0.6226 - accuracy: 0.6047 - val_loss: 0.5896 - val_accuracy: 0.6	8905 - 1r: 0.0010
	Epoch 4/30	Ac 380mc/ct	- loce: 0 5065 - accumacus 0 7631 - val loce: 0 5636 - val accumacus 0 (	0000 - 101 0 0010
	Epoch 5/30		- Iossi elsees - accaracyi elses - tar_tessi elsese - tar_accaracyi els	reso - in orocio
	14/14 [	] - 4s 274ms/ste	) - loss: 0.5582 - accuracy: 0.8142 - val_loss: 0.5326 - val_accuracy: 0.9	9381 - lr: 0.0010
	Epoch 6/30			
	14/14 [====================================	/] - 55 337ms/ste	- 1055: 0.5393 - accuracy: 0.7669 - Val_1055: 0.4970 - Val_accuracy: 0.8	5286 - 1r: 0.0010
	14/14 [====================================	1 - 4s 284ms/sto	- loss: 0.5032 - accuracy: 0.8000 - val loss: 0.4800 - val accuracy: 0.0	9429 - 1r: 0.0010
	Epoch 8/30			
	14/14 [	] - 4s 297ms/ste	) - loss: 0.4760 - accuracy: 0.8521 - val_loss: 0.4367 - val_accuracy: 0.8	8714 - lr: 0.0010
	Epoch 9/30	l Ac 315mc/ct/	- loss: 0 4405 - accupacy: 0 9630 - val loss: 0 4209 - val accupacy: 0 (	0049 - 10: 0.0010
	Epoch 10/30	interest of the stampace	- Tossi binnes - accuracy, binoss - Var_toss, binzos - Var_accuracy, bin	0040 - 111 010010
	14/14 [	] - 4s 299ms/ste	) - loss: 0.4262 - accuracy: 0.8580 - val_loss: 0.3982 - val_accuracy: 0.9	9048 - lr: 0.0010
	Epoch 11/30			
	14/14 [====================================	] - 4s 287ms/ste	- loss: 0.4335 - accuracy: 0.8604 - val_loss: 0.3648 - val_accuracy: 0.8	3762 - 1r: 0.0010
	14/14 [	1 - 5s 314ms/st(	- loss: 0.4245 - accuracy: 0.8154 - val loss: 0.3720 - val accuracy: 0.0	8381 - lr: 0.0010
	Epoch 13/30	,		
	14/14 [	] - 4s 311ms/ste	) - loss: 0.3741 - accuracy: 0.8769 - val_loss: 0.3597 - val_accuracy: 0.9	9095 - lr: 1.0000e-04
	Epoch 14/30	1 - 4s 385ms (stu	- less: 0.3503 - accupacu: 0.0173 - val less: 0.3455 - val accupacu: 0.0	1005 - 101 1 00000-04
	Epoch 15/30		- Tossi bissoz - accuracy: bist/z - Vat_Tossi bisass - Vat_accuracy: bie	3905 - 111 1:00000-04
	14/14 [	] - 4s 296ms/str	) - loss: 0,3568 - accuracy: 0.8935 - val_loss: 0,3428 - val_accuracy: 0.8	8857 - lr: 1.0000e-04
	Epoch 16/30			

The image shows that Define Callbacks function

lr\_callback = callbacks.ReduceLROnPlateau(monitor='val\_accuracy', factor=0.1, patience=5)
stop\_callback = callbacks.EarlyStopping(monitor='val\_accuracy', patience=10)FIGURE 11

Т

![](_page_7_Picture_0.jpeg)

![](_page_7_Picture_1.jpeg)

The above figure shows the testing on test dataset using ResNet50 algorithm and finding all diabetic abnormal ulcer .

# FIGURE 12

![](_page_7_Figure_4.jpeg)

The above chart shows the history model accuracy on epoch and accuracy on basis of training and validation of diabetic foot ulcer.

![](_page_8_Picture_0.jpeg)

![](_page_8_Figure_2.jpeg)

The above figure shows the segmenting of diabetic foot ulcer an predicting wheather normal or abnormal ulcer.

# **III) Conculsion:**

Diabetic foot ulcer can be frequently monitor avoid amputation of leg by using deep learning approach using ResNet50 algorithm . Deep neural network models are explored for the automatic classification of diabetic foot images into normal (healthy skin) and abnormal (DFU). ResNet50 based model has better than other CNN models like Google Net, Alex Net, VGG16, VGG19 on diabetes foot ulcer image set.

L

![](_page_9_Picture_0.jpeg)

## REFERENCES

- 1. **Deep Learning in Diabetic Foot Ulcers Detection: A Comprehensive Evaluation** Moi Hoon Yapa,\*, Ryo Hachiumab,1, Azadeh Alavic,1, Raphael Brungel."
- Article A Deep Learning Approach for Diabetic Foot Ulcer Classification and Recognition Mehnoor Ahsan 1, Saeeda Naz 1,\*, Riaz Ahmad 2, Haleema Ehsan 1 and Aisha Sikandar 1
- Diabetic foot ulcer detection using deep learning approaches Author links open overlay panelPuneeth N. Thotad <sup>a b</sup>, Geeta R. Bharamagoudar <sup>c</sup>, Basavaraj S. Anami <sup>d</sup>
- **4.** Early detection of diabetic foot ulcers from thermal images using the bag of features technique Author links open overla panelMohammaH. Alshayeji <sup>a</sup>, Silpa ChandraBhasi Sindhu<sup>b</sup>, Sa'ed Abed<sup>a</sup>
- Deep learning in diabetic foot ulcers detection: A comprehensive evaluation Author links open overlay panelMoi Hoon Yap <sup>a</sup>, Ryo Hachiuma <sup>b</sup>, Azadeh Alavi <sup>c</sup>, Raphael Brüngel
- <sup>6.</sup> Recognition of ischaemia and infection in diabetic foot ulcers: Dataset and techniques Author links open overlay panel Manu Goyal <sup>a</sup>, Neil D. Reeves <sup>b</sup>, Satyan Rajbhandari <sup>c</sup>, Naseer Ahmad <sup>d</sup>, Chuan Wang <sup>e</sup>, Moi Hoon Yap <sup>a</sup>
- 7. A machine learning model for early detection of diabetic foot using thermogram images Author links open overlay panelAmith Khandakar <sup>a b</sup>, Muhammad E.H. Chowdhury <sup>a</sup>, Mamun Bin Ibne Reaz <sup>b</sup>, Sawal Hamid Md
- 8. DFU\_SPNet: A stacked parallel convolution layers based CNN to improve Diabetic Foot Ulcer classification Author links open overlay panelSujit Kumar Das, Pinki Roy, Arnab Kumar Mishra
- 9. DFUNet: Convolutional Neural Networks for Diabetic Foot Ulcer Classification Manu Goyal, Student Member, IEEE, Neil D. Reeves, Adrian K. Davison, Member, IEEE, Satyan Rajbhandari, Jennifer Spragg, and Moi Hoon Yap, Member, IEEE
- Automatic Scoring of Diabetic foot Ulcers through Deep CNN based Feature Extraction with Low Rank Matrix Factorization 1st Chathurika Gamage dept. of Computer Science & Eng. University of Moratuwa Moratuwa (10400), Sri Lanka chathuri.12@cse.mrt.ac.lk 2nd
- Deep learning in diabetic foot ulcers detection: A comprehensive evaluation Author links open overlay panelMoi Hoon Yap <sup>a</sup>, Ryo Hachiuma <sup>b</sup>, Azadeh Alavi <sup>c</sup>, Raphael Brüngel <sup>d g</sup>
   B. Ascher <sup>c</sup>, Anping Song <sup>f</sup>, Hiroki Kajita <sup>h</sup>, David Gillespie <sup>a</sup>, Neil
   D. Reeves <sup>a</sup>, Joseph M. Pappachan <sup>i</sup>, Claire O'Shea <sup>j</sup>...Eibe Frank <sup>k</sup>
- 12. Area determination of diabetic foot ulcer images using a cascaded two stage svm based classification. Lei Wang1, Peder C. Pedersen1, Emmanuel Agu2, Diane Strong3

Ι

![](_page_10_Picture_0.jpeg)

- 13. Robust Methods for Real-Time Diabetic Foot Ulcer Detection and Localization on Mobile Devices Manu Goyal, Student Member, IEEE, Neil D. Reeves, Satyan Rajbhandari, and Moi Hoon Yap, Member, IEEE
- 14. Analysis of Thermal Images with Parallel Convolutional Deep Neural Network for Diabetic Foot Detection Jayaprakash Katual; Amit Kaul
- 15. A Deep Learning framework and its Implementation for Diabetic Foot Ulcer Classification Madhava S Prabhu; Seema Verma
- 16. Diabetic Foot Ulcer Ischemia and Infection Classification Using EfficientNet Deep Learning Models Ziyang Liu; Josvin John; Emmanuel Agu
- 17. Identification of Diabetic Foot Ulcer in Images using Machine Learning Shalok Mohanty; Silky Goel; Rahul Nijhawan; Siddharth Gupta
- FusionSegNet: Fusing global foot features and local wound features to diagnose diabetic foot Tiancai Lan<sup>a</sup>,
   Zhiwei Li<sup>b</sup>, Jun Chen

Т