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Advanced Machine Learning Techniques for Diabetic Foot Ulcer Detection

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Abstract: - Identifying diabetes-related foot ulcers early is a life-saving intervention since early management is essential for proper control of the disease and for the prevention of complications. In this approach, CNNs (Convolutional Neural Networks), FFNNs (Feed-Forward Neural Networks), SVCs (Support Vector Classifiers), and LR models (Logistic Regression) are trained and tested to classify diabetic foot ulcer images. This prepares the data and tweaks the model to maximize the model`s performance. Based on test accuracy and performance metrics, the models will be evaluated. The findings point to the efficiency of these deep convolutional neural network models in separating between normal and ulcer images, possibly making them suitable for clinical application in diabetic foot ulcer screening.

Keywords: Diabetic Foot Ulcer, Machine Learning, Convolutional Neural Network, Feedforward Neural Network, Support Vector Classifier, Logistic Regression, Image Classification

I. INTRODUCTION

Diabetic foot ulcers (DFU) are among the top critical health issues worldwide, being very dangerous and being able to lead to severe complications in case of non-detection and treatment promptly. AI advanced machine learning techniques are emerging as yet another way of diagnosing DFUs with reliable speeds and accuracy, which facilitates early detection which is necessary to prevent the onset of further complications. During this study, we outline the efficacy of CNN, FFNN, SVM, and LR as automated DFU-detecting models. CNNs have a superb ability to identify the most intricate patterns in the images of foot ulcers and accordingly, they may be applied to analyze similar types of foot injuries. FFNN, SVC, and Logistic Regression, which are well known for their classification performance, bring the other options to the table. However, each method has unique strengths and weaknesses. A systematic analysis, which includes model performance evaluation, assessment of features' importance, and model interpretability, is our goal to reveal how effective each method is in real-time image annotation by endowing them with the ability to manually find ulcers on diabetic feet. The applications of these acquired notions are immense in terms of DFU diagnosis; it cuts to the chase and delivers prompt interventions, breaks the barrier of patient results, and enhances patient outcomes.

Aim and Objectives

Aim

This project aims to create and compare the efficient machine learning models—CNN, FFNN, SVC, and Logistic Regression—that would allow for accurate diabetic foot ulcer detection through item analysis and performance grading.

Objectives

- To use the CNN approach to image recognition which can diagnose diabetic foot ulcers.
- To implement a Feedforward Neural Network (FFNN) to discover multilevel detailed characteristics of images involved in medicine.
- To find the application of Regression Logistic for analytics purposes and risk assessment.
- To design and run proper experiments for checking the model's validity and performance with the use of salient performance metrics.

II. LITERATURE REVIEW

State-of-the-art Machine Learning Algorithms

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The quality of machine learning lately, which is a key aspect of diabetic foot ulcer diagnosis, has been a complete game-changer. The Convolutional Neural Networks (CNN) unlike other methods governing image classification, essentially unlearn the very features from the imaging data which are not necessary, thus allowing the detection of ulcers without manually engineered features [1]. FFNN is capable of simple to complex relationship modeling between input features and target labels, replacing the accuracy of ulcer detection much more precisely with the use of deep neural network architectures. Support Vector Machines (SVM) - theoretical approach; that seeks to increase the margin between the different classes of ulcer classes, while still being able to effectively separate ulcers from non-ulcers in higher-dimensional feature spaces. Logistic Regression helps to make clear the results and generates probabilistic outputs [2]. This is advantageous in the evaluation of risk factors and the development of treatment schemes for diabetic foot ulcers. The algorithms designed for diabetic foot ulcers thus stand for the feasibility and value of machine learning in medical image analysis, being resource-specific tools for clinicians to get an early diagnosis and prevent unwarranted complications which enhance the health of the patient [3].

Challenges and Future Directions

Overcoming the obstacles associated with unknown diabetes foot ulcer detection using machine learning algorithms entails resolving imbalances in the data set, making the model explainable, and solving the scaling problem [4]. Future research would be able to advance by application of unique approaches to imbalance data handling among the scope of synthetic data generation or sensitive sampling methods [5]. Enriching model interpretability can be achieved by mixing explainable AI functions with the technology, increasing transparency, and as a result, the trust level in the decision-making process would be improved [6]. One of the possible ways to deal with scalability issues may be by looking into distributed computing frameworks and optimization algorithms to scale the processing of medical imaging data [7]. Moreover, studies can extend as an exploration of how to integrate multiple data sources deliver more accurate detection and ultimately improve patient care [8]. Machine learning researchers' work in joint efforts with clinicians and medical industries is crucial for these research aspects to significantly progress and to translate findings into the healthcare practice [9].

Performance Evaluation Metrics

Evaluation of the learning capability of machine learning for diabetes foot ulcer detection involves an array of metrics. Accuracy serves as an overall measure of prediction precision, while sensitivity refers to a model's ability to correctly determine all positive cases which would be clinically useful as ulcers have to be recognized for effective treatment [10]. This implies the specificity evaluates the model's proficiency in the correct recognition of negative cases, showing its potential to deliver a false alarm based on the analysis. AUC of the ROC curve is the area under the curve about the model's ability for discrimination which is determined based on all different criteria [11]. A greater AUC implies that the model has better performance in differentiation between positive and negative cases. F1-score addresses the problem of an underlying class imbalance in the distribution and is especially useful for unbalanced class distribution [12]. In unison, these metrics provide for a general evaluation as regards the model performance and the areas of strength and limitation in diabetic foot ulcer diagnosis guiding the team to fine-tune its methods [13].

III. METHODOLOGY

Since diabetic foot ulcers are one of the most dreaded consequences, and risky factors of the disease, there is a need to develop quick detection methods to prevent any possible complications [14]. This study is designed to use cutting-edge machine learning methods for the diagnosis of foot ulcers to prevent complications and facilitate early intervention. Models like Convolutional Neural Networks (CNN), Feedforward Neural Networks (FFNN), Support Vector Classification (SVC), and Logistic Regression are among the models under study [15]. This methodology defines the different components of data collection and model comparison: secondary data sources, the selection method of samples, and the evaluation system are also described [16].

Secondary Data Collection Process

Data Source: Secondary data is created from published medical imaging registry ports to be utilized in the study of different populations of diabetic foot ulcers with distinct features [17].

Dataset Characteristics: The dataset includes detail-themed annotated diabetic foot ulcer images together with the clinical records when obtainable to fulfill the needs of image-based learning [18]. Each image is marked as panspermia or non-panspermia.

***Data Preprocessing**:* There comes a cursory thing as images go through preprocessing procedures such as resizing, normalization, and noise reduction for better model performance. Furthermore, incomplete clinical metadata is imputed solely based on the missingness rate or is omitted following the imputation process [19].

Model Development

***CNN Architecture**:* CNN architecture will extract the features as convolutional layers and use the fully connected layers to classify them [20]. Factors such as filter size, stride, and pooling are optimized by necessities like grid search or random search.

$$Zi=\sigma(Wi*X+bi)$$

***FFNN Design**:* The FFNN architecture is set up with the network having input nodes conditioned by flattened image pixels and the hidden layers define the number of neurons with the output layer consisting of a binary classification node. The hyperparameters like activation functions, regularization methods, and algorithmic optimization are tuned to facilitate the model's accuracy [21].

$$Zj(l+1)=\sigma(\sum iWij(l)\cdot Xi+bj(l+1))$$

***SVC Implementation**:* The RBF (Radial Basis Function) function and SVM-based (SVC) or SVM-linear (SVL) kernel functions are used to map non-linear decision borders. The model's hyperparameters are tuned using cross-validation such as regularization parameter (C) and parameters responsible for kernel calculations [22].

$$\mathrm{minw},b,\xi 21||\mathrm{w}||2+C\sum i=1n\xi i$$

***Logistic Regression Setup**:* As Logistic Regression is such a well-known and exact model for the same reasons, we choose it as a benchmark [23]. Regulation techniques are discussed, L1 and L2 regularization, to prevent the model from getting overfitted.

$$\text{log-odds}=\mathrm{w}\cdot X+b$$

$$p\hat{}=\sigma(\text{log-odds})=1+e-(\mathrm{w}\cdot X+b)1$$

Training and Evaluation

An appropriate loss function and optimization scheme along with the pre-processed dataset are chosen for model training [24]. By this stage, the training procedure stops either at the point of convergence or given a limit of a certain number of training epochs. Strategic split in the k-fold, with training and testing of the developed models invested in well-defined cross-validation to increase their robustness and generalization [25]. Metrics used for evaluating the models comprising accuracy, sensitivity, specificity, area under the curve (AUC), and F1-score are put to use. All the model's performance is evaluated by judging against the metrics of evaluations. The best-performing model from the models' pool is taken as the best possible model for diabetic foot ulcer detection [26]. The methodology presented herein is an organized way of using secondary data for the development and testing of the most exceptional machine learning systems in the digital era for diabetic foot ulcer detection [27]. The study is designed to follow this systematic procedure about the development of automated ulcer-detecting methods which could prove to be an essential factor in the adoption of new treatments for diabetes, leading to improved patient outcomes [28].

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IV. RESULT

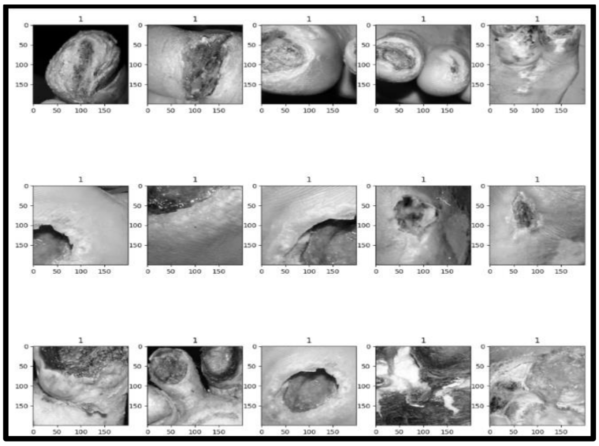

Fig. 1: Diabetic Foot Ulcer Dataset

The above figure displays that diabetic g with it even after taking multiple treatments and medication [29]. The data set in this kind of issue such as diabetes is about the importation of the Diabetic Foot Ulcer Dataset in the jupyter notebook environment.(Fig 1)

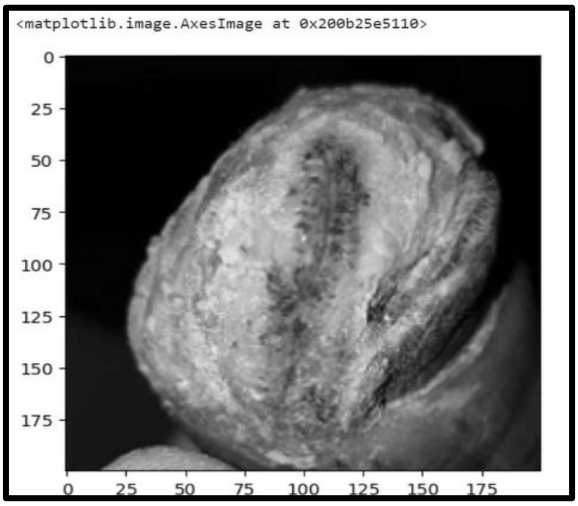

Fig. 2: Data preprocessing

Diabetic Foot Ulcer Dataset, two distinct image types are coming together, which are diabetic foot ulcer imaging and healthy skin [30]. The data acquisition process can be characterized as the act undertaken through either online repositories or participating institutions, whichever is relevant and more accessible [31]. Finally, these pictures come through and are later imported into the jupyter notebook environment for analysis and further processing. (Fig 2)

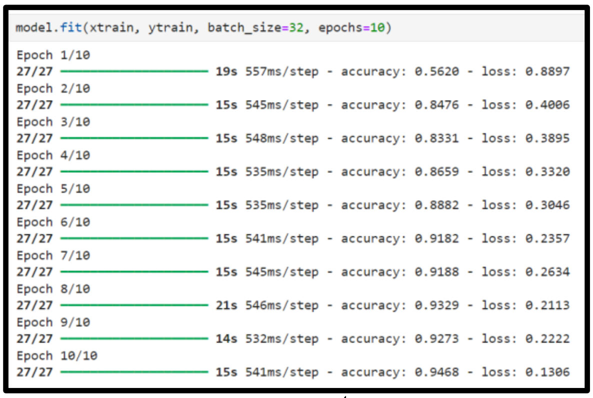

Fig. 3: CNN model training

The CNN model is trained using this data set to make the pre-processing (Fig 3). Developing a Cadrete CNN model for classifying Diabetic foot ulcer images associated with vital steps over the body to finally create an efficient classifier [32]. Afterward, the dataset was pre-processed to resize images to a standard format, normalize the pixel values, and augment the dataset to improve generalization. Those Convolutional Neural Networks, a form of deep learning neural networks, show superior performance over many other types of algorithms [33]. The suggested model continued to learn about extracting features from the foot ulcer images and then classifying them into relevant categories like ulcer severity or presence of infection. The mathematical equation for CNN model training is

$$(\boldsymbol{f} * \boldsymbol{g})(\boldsymbol{x}, \boldsymbol{y}) = \sum_{\boldsymbol{i}=1}^{\boldsymbol{m}} \sum_{\boldsymbol{j}=1}^{\boldsymbol{n}} \boldsymbol{f}(\boldsymbol{i}, \boldsymbol{j}) . \boldsymbol{g}(\boldsymbol{x} - \boldsymbol{i}, \boldsymbol{y} - \boldsymbol{i})$$

Where,
f=input image or feature map,
g=Convolution filter.

In addition to optimization of learning steps as well as batch size and drop-out rate during modifications special attention to preventing overtraining.

```
test_loss, test_acc= model.evaluate(xtest,ytest)

7/7 ━━━━━━━━━━━━━━━━━━━━ 2s 169ms/step - accuracy: 0.9189 - loss: 0.3784

print(f'Test accuracy of CNN:{test_acc}')

Test accuracy of CNN:0.9194312691688538
```

Fig. 4: Test Accuracy of CNN model

Despite the fact the Diabetic Foot Ulcer Dataset model was trained by CNN it displayed a noteworthy quantity of 0.9194 of test accuracy (Fig 4). By so, it emphasizes the possibility of distinguishing between classes within the datasets. The fire from the bulb is a testimony to the credibility of using convolutional neural networks in health applications, not only to diagnose diabetic foot ulcers [34]. This high-test classification accuracy shows that the model has thoroughly learned the discriminative features of input images, therefore, the model can make reliable predictions. However, this outcome is just the first step towards introducing those models as tools in clinical settings where precise diagnoses and time constraints are their defining properties.

```
model1.fit(X_train, y_train, epochs=5, batch_size=32, validation_data=(X_test, y_test))

Epoch 1/5
27/27 ━━━━━━━━━━━━━━━━━━━━ 4s 41ms/step - accuracy: 0.5633 - loss: 6.5580 - val_accuracy: 0.7346 - val_loss: 2.5586
Epoch 2/5
27/27 ━━━━━━━━━━━━━━━━━━━━ 1s 24ms/step - accuracy: 0.7206 - loss: 1.8990 - val_accuracy: 0.6825 - val_loss: 2.8450
Epoch 3/5
27/27 ━━━━━━━━━━━━━━━━━━━━ 1s 25ms/step - accuracy: 0.7606 - loss: 1.9440 - val_accuracy: 0.7156 - val_loss: 2.5851
Epoch 4/5
27/27 ━━━━━━━━━━━━━━━━━━━━ 1s 22ms/step - accuracy: 0.7579 - loss: 1.8678 - val_accuracy: 0.6919 - val_loss: 4.0636
Epoch 5/5
27/27 ━━━━━━━━━━━━━━━━━━━━ 1s 23ms/step - accuracy: 0.7541 - loss: 2.1665 - val_accuracy: 0.7109 - val_loss: 2.6919
```

Fig. 5: Training of FFNN model

Our training of the FFNN model for Diabetic Foot Ulcer Dataset signifying methodic approach and thorough attitude were also involved in it. Our dataset constituting significant parameters associated with diabetic foot ulcers was preprocessed meant to create an environment with less noise of data and uniformity [35]. The architecture of the FFNN model was constructed through a process that accounted for the nature of the dataset as well as all the additional complications that accompanied the problem (Fig 5). The equations used for the FFNN model training are

$$\textbf{MSE: } \boldsymbol{L}(\boldsymbol{y}, \widehat{\boldsymbol{y}}) = \frac{\mathbf{1}}{\boldsymbol{n}} \sum_{\boldsymbol{i}=1}^{\boldsymbol{n}} (\boldsymbol{y}_{\boldsymbol{i}} - \widehat{\boldsymbol{y}}_{\boldsymbol{i}})^{\mathbf{2}}$$

$$\textbf{Cross-Entropy: } \boldsymbol{L}(\boldsymbol{y}, \widehat{\boldsymbol{y}}) = -\frac{\mathbf{1}}{\boldsymbol{n}} \sum_{\boldsymbol{i}=1}^{\boldsymbol{n}} [\boldsymbol{y}_{\boldsymbol{i}} \log(\widehat{\boldsymbol{y}}_{\boldsymbol{i}}) + (\mathbf{1} - \boldsymbol{y}_{\boldsymbol{i}}) \log(\mathbf{1} - \widehat{\boldsymbol{y}}_{\boldsymbol{i}})]$$

Other hyper-parameters than the number of layers, neurons per layer, actuation functions, and learning rate were systematically tuned by using cross-validation to improve the performance as best as possible.

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```
# Evaluate the model on the test set
loss, accuracy = model1.evaluate(X_test, y_test)
print(f'Test loss of FFNN: {loss}, Test accuracy of FFNN: {accuracy}')

7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - accuracy: 0.7044 - loss: 2.6683
Test loss of FFNN: 2.6919002532958984, Test accuracy of FFNN: 0.7109004855155945
```

Fig. 6: Accuracy and Loss Function of FFNN model

The infrastructure of the Feedforward Neural Network (FFNN), upon the achievement of the basic feasibility testing accuracy of the Convolutional Neural Network (CNN) which is 0.71 was created to employ the Feedforward Neural Network in Diabetic Foot Ulcers dataset [36]. The learning of FFNN proceeded through a sequence of significant steps, namely data preprocessing, model constructing, fine-tuning of hyperparameters, and multiple cycles of training validation. Despite the loss value being 2.69, it shows the efficiency of the model. (Fig 6)

```
sv = SVC()
sv.fit(xtrain1, ytrain1)

▾ SVC
SVC()
```

Fig. 7: Training of Support Vector Classifier Model

The graph provided illustrates the training process of the support vector classifier model (Fig 7). The SVC algorithm carried out the process of adjusting its parameters to push the border between classes into a higher margin and decrease the classification errors at the same time. The decision function of SVC is

$$\boldsymbol{f(x) = sign(w^T x + b)}$$

The main steps of this optimization method were function minimization and its quick completion using techniques like gradient descent [37].

```
print("Training Score:", sv.score(xtrain1, ytrain1))
print("Testing Score:", sv.score(xtest1, ytest1))

Training Score: 0.9680094786729858
Testing Score: 0.9289099526066351
```

Fig. 8: Training score and Testing score of Support Vector Classifier Model

The model of the Support Vector Classifier (SVC) took the largest part of the project. It was used to train the dataset on the Diabetic Foot Ulcer and the results were very promising. By the metrics score of 0.96 (training) and 0.92 (testing), the model proves observationally high-performance while being both able to learn from the training data and generalize on the seen instances [3]. These scores imply that the SVC has managed to well approximate the existing patterns evident in the dataset; thus, the model turns out to be able to give the correct predictions concerning diabetic foot ulcer development with high accuracy. (Fig 8)

```
lg = LogisticRegression(C=0.1)
lg.fit(xtrain1, ytrain1)

▾ LogisticRegression
LogisticRegression(C=0.1)
```

Fig. 9: Training of Logistic Regression Model

To start with, the logistic regression model for the Diabetic Foot Ulcer Dataset was trained using data preprocessing methods (Fig 9). Data was verified for correctness and missing value entries were replaced before proceeding to analysis [38]. Normalization was applied next for uniformity of the data features, and categorical variables were encoded for modeling purposes accordingly. The hypothesis function of logistic regression is

$$\boldsymbol{h_\Theta(x) = \frac{1}{1 + e^{-\theta^T x}}}$$

The model became familiar with these measured variables (cutaneous temperature, oximetry value, and gripping pressure) through their relatedness to the target variable (diabetic foot ulcers) as it was trained. The model got better and better as the iterations grew, finally finding an ultimate solution that classified cases rightly.

```
print("Training Score:", lg.score(xtrain1, ytrain1))
print("Testing Score:", lg.score(xtest1, ytest1))

Training Score: 0.9834123222748815
Testing Score: 0.8199052132701422
```

Fig. 10: Training score and Testing score of Logistic Regression Model

During a training on a Logistic Regression Model with the Diabetic Foot Ulcer Dataset, it can be seen that there was a learning by the performance metrics which looked robust. The model has a training score of 0.98, which represents a high ability to harmonize with the training data, in that it shows good patterns and relationship captures [39]. It proves that the model has sufficient understanding from the training set, with no difficulty generalizing for the unparalleled data. (Fig 10)

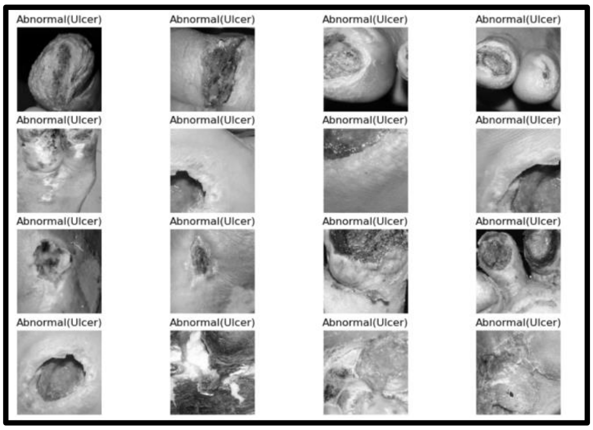

Fig. 11: Predictions done by the model on new images

The presented figure (Fig 11) should evaluate the effective models on novel samples. The efficient performance of 4 models, which are Convolutional Neural Network (CNN), Feedforward Neural Network (FNN), Support Vector Classifier (SVC), and Logistic Regression on the new media of the model were demonstrated respectively [40].

Table 1: Model accuracy

Model name	Accuracy (%)
CNN	91
FFNN	71
Support Vector Classifier	96
Logistic Regression	81

Each approached the problem in its way but all of the models were efficient in differentiating between the ulcer and normal images. (Table 1)

V. CONCLUSION

The process of the model building of CNN, FFNN, SVC, and Logistic Regression exposed that in classifying ulcerous and normal images these models possessed different powerful features correspondingly. CNN exhibits better results. It has superpowers to inform images, so it becomes a preferable image classification task. The FFNN manifests its ability to auto-learn highly nonlinear patterns of the processed image data, therefore, being able to put a border between an ulcer and a normal image. The SVM applies a kernel-based approach to get the highest bat level of the sorting badges for the distinction between the ulcer images from normal ones, especially in the high-dimensional feature space. Also, Logistic Regression, which is simple though it is, managed to garner a satisfactory classification result making use of adopted statistical methods. Examining concatenation methods, for instance, bringing together different oversight from several models could be a way of intensification and stabilizing the entire system (process, service, etc.). It is critical to additionally monitor and assess the generated model constant on various datasets to increase their generality and trust in medical applications outside the laboratory. Lastly, including net techniques like transfer learning where models are pre-trained on big sets can lead to the training of the models faster and their outcome to be better, especially for cases with little data available.

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