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A HYBRID DEEP CNN-LSTM NETWORK (HDCLN) FOR SHOULDER IMPLANT CLASSIFICATION USING X-RAY IMAGES

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ABSTRACT

Today, prosthesis manufactured from polyethelene and metallicconstituents have been widely used to replace the impaired ball and sockets of the human shoulder. Years after the replacement, there may be need for reoperation and revision due todesecration in the quality of the prosthesis. This process requires the information about the prototype as well as the corresponding manufacturer of the prosthesis. In some situations, the patient and the primary doctor may not have the information about the prototype and manufacturer of the prosthesis. Usually, manual recognition of the prototype and manufacturer of the prosthesis is carried out during the preoperative planning. However, the manual identification of the model and manufacturer is time-consuming and prone to error. An automatic model identification and manufacturer classification system can speed up the treatment process and reduce the operation risk associated with the manual identification system.In this paper, we introduce a hybrid deep CNN-LSTM network for identification and classification of implant manufacturer. In this network, we used the CNN layer to extract features from the radiographic images and the LSTM layer for identification and classification of implants. A collection of 597 implant images from four manufacturers, including 83 images from Cofield, 294 from Depuy, 71 from Tornier, and 149 from Zimmer, were used as dataset to train and test the model. Based on experimental results, our model achieved the accuracy of 98.7%, precision of 98%, F1-score of 98.2% and recall of 98%. Based on the performance of the model, we believe that this model will be a useful tool in preoperative planning and can be applied in the identification and classification of implants from other manufacturers.
Keywords: *CNN-LSTM, Manufacturer, Classification, Shoulder Arthroplasty*

1. INTRODUCTION

Total Shoulder Arthroplasty has been widely used in treating damaged shoulder joints [1]. Common causes of shoulder damage and malfunctioning include: injuries, calcification, impairment in the shoulder cartilage tissue, damage to nearby bones, and severe arthritis. This damage results in severe trauma and malfunction of the shoulder. When the damage to the shoulder joint persists, a surgical process may be employed to mitigate pains and re-establish movement in the patient shoulder [1, 2]. In TSA procedure, the damaged joint is detached and replaced with artificial prosthetic joint [3]. X-ray implant graphics are employed to determine the fitness of the artificial prosthesis prior to the surgery and evaluate the accuracy of the placement of the artificial prosthesis after the surgical process.

Currently, there exist various makers of shoulder prosthesis that make different models of this prosthesis to well fit various situations and patients [22]. Years after the replacement, there may be need for reoperation and revision when the quality of the prosthesis degrades. The major surgical step to minimize the common complications is the identification of the model, structure, and manufacturer of prosthesis to properly position them. In situations where a patient migrates from the location or country of surgery, the patient and the primary physician in the other location or nation may be unaware of the model and manufacturer of the prosthesis. Thus, a rigorous examination and visual comparison of radiographic images [22] is required to identify the model of the prosthesis and as well as the manufacturer. This approach is time consuming and prone to error, in addition to delay in reoperation and revision.

Many researchers have demonstrated various deep learning techniques [9] to identify the model, structure of implants and classify them based on their respective manufacturers. Recently, ResNet [4], Convolutional Neural Network (CNN) [5-7, 10, 11], Neural Network [8], VGG [12], GoogleNet [13], Inception [11], and other deep learning approach have been used to automatically detect implant manufacturer. These methods have been employed as feature extractors that enhance implant detection and classification accuracies.

This paper developed a hybrid deep CNN+LSTM paradigm for identification and classification of implant manufacturer. In this network, we used the CNN layer to draw out features from the radiographic images and the Long Short Term Memory layer for identification and classification of implants. A collection of 597 implant images from four manufacturers, including 83 images from Cofield, 294 from Depuy, 71 from Tornier, and 149 from Zimmer, were employed as dataset to train and evaluate the proposed hybrid model.

The summary of the contributions of this paper are presented below:

- To develop a hybrid deep CNN+LSTM paradigm for automatic detection and classification of prosthesis based on manufacturer.
- To develop a model that minimizes the time taken and error in the traditional method of prosthesis identification and classification.
- To evaluate the efficiency of the developed hybrid deep CNN-LSTM on shoulder implant radiographs

The remainder of this paper is structured to have the following sections: section 2 review works done by researchers in identification and classification of implants manufacturer. The detail explanation of the developed model is presented in section 3 of this paper. In section 4, we present the details of the experiment and the results obtained while training and testing our model. Lastly, we conclude this paper and explain our future research direction in section 5.

2. RELATED WORK

This section of the article presents the recent work done on identification and classification of implants manufacturers using radiographic images.
Authors in [22] proposed a custom Convolutional Neural Network model for shoulder implants classification based on manufacturer. The model achieved a promising result as benchmarked with the pre-trained models"VGG-16, VGG-19, ResNet-50, ResNet-152, DenseNet, and NasNet". Authors in this paper collected shoulder implant images from different manufacturers in order to train their model.
In [23], authors proposed an automatic Total Shoulder Arthroplasty (TSA) implant detection and segmentation using X-Ray images. In this work, authors applied the though transform method to locate the implant and then apply simple seeded region growing for image segmentation. This method achieved a promising result with the accuracy of 94%.
In [24], authors applied You Only Look Once (YOLO3) version 3 algorithm on panoramic radio graph images with six implants from three manufacturers. This method achieved the accuracy of 72%.
In [25], authors segment the panoramic implant images and then use the traditional pre-trained models (VGG-16 and VGG-19) by employing transfer learning concept to classify the wide implant graphics. However, the VGG-16 and VGG-19 network in this work fails to detect the un-cropped panoramic implant images.

3. PROPOSED METHOD

The developed hybrid system for detection and classification of shoulder implants consists of three main phases as illustrated in figure 1. In the preprocessing phase, the raw implants X-ray images were resized, shuffled, and normalized to resolve the variation in resolution of the implant X-preprocessing pipeline was further divided into training dataset and test dataset. The training dataset constitute 80 percent of the larger dataset and the test dataset constitute 20 percent of the larger dataset. Both training and test dataset were passed to the feature extraction phase at the time of training and evaluation. In the feature extraction phase, implant features were drawn out from the preprocessed implant X-ray images using Convolution Neural Network (CNN). In the classification phase, the features extracted from the feature extraction phase are used to identify the correct manufacturer of the implant. The training dataset from the pre processing pipeline was used to train the developed model and the corresponding training accuracy and training loss were monitored. Also, the conventional 5-fold cross validation approach is employed in validating the developed model and the corresponding validation accuracy and validation loss were monitored. The efficiency of the developed hybrid deep CNN-LSTM method was evaluated based on the following metrics: model accuracy, precision, recall and F1-score.

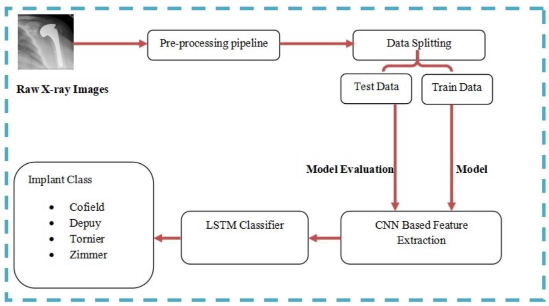


Fig. 1. Architecture of the Implant Detection Model

3.1. Convolution Neural Network (CNN)

CNN is a feed forward neural network that shows promising achievements in applications like DIP, objected detection [15], NLP [14], and medical image analysis. As illustrated in figure 2, a typical CNN comprise of convolution layer, down sampling (pooling) layer and FC (Fully Connected) layer. In CNN, local features from higher convolution layer input are forwarded to the lower convolution layer input for more convoluted features. Each convolution layer consists of a number of kernels for determining a tensor of feature map. The working of the Conv Layer is given in equation 1.

$$y_t = k(x_t * w_t + b_t) \quad (1)$$

Where y_t is the output of the convolution layer, k is the activation function, x_t is the input vector, $w_t$and $b_t$are the weightand the bias of the kernel.The activation function is used to make the feature maps more nonlinear. By maintaining the threshold input at zero, the Rectified Linear Unit (ReLU) is widely employed to compute activation.. This operation is given as:

$$f(x) = \max(0, x) \quad (2)$$

The dimensions of the features extracted by the convolution layer are very huge. To address the dimensionality problem in the convolution layer and minimize the network training cost, a pooling layer is introduced. The pooling layer down samples the output of the preceding convolution layer to down sample the size of the parameters.

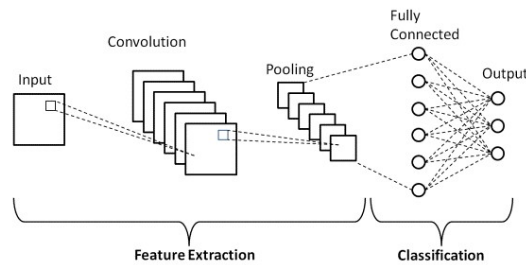
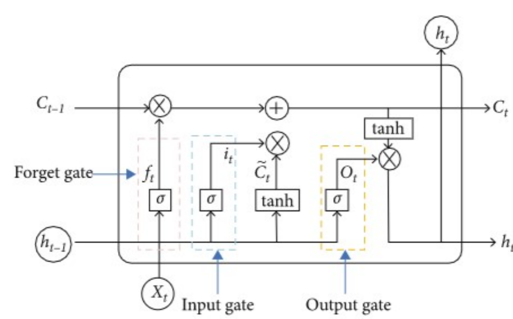


Fig. 2. Architecture of CNN

3.2. Long Short Term Memory

LSTM is an enhancement of the conventional RNN designed to address the long standing issue of vanishing and gradient explosion [16-18]. Due to the memory in LSTM and its ability to make relatively accurate forecasting, it shows promising performance in applications like speech recognition, text analysis and emotional analysis. The main difference between the conventional RNN and LSTM is the cell state used to save long-term state.The LSTM memory cell comprises of three gates: the input gate, the forget gate and the output gate as illustrated in fig. 3.



From fig. 3, $x_t$represent the present input, C_t and C_{t-1}represents the present and prior cell state. $h_t$and h_{t-1}represents the present and prior output.

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The operation of LSTM is given as follows:
First, the output of the last time step $h_{t-1}$and the input value of the current time step$x_t$are fed into the input gate (tanh layer). The current time step information, $\widetilde{C}_t$, and the output value of the input gate are determined as follows:

$$i_t = \sigma(W_i . |h_{t-1}, x_t| + b_i) \quad 3$$

$$\widetilde{C}_t = tanh(W_i . |h_{t-1}, x_t| + b_i) \quad 4$$

Where $i_t \in (0, 1)$, W_i and b_i represents weight and bias respectively.
The current cell is then updated as follows:

$$C_t = fC_{t-1} + i\widetilde{C}_t \quad 5$$

With a specific probability, the choice to forget or keep associated information from the prior cell state is made as follows:

$$f_t = \sigma\left(W_f . |h_{t-1}, x_t| + b_f\right) \quad 6$$

The final output $O_t$of the output gate is determined as follows:

$$O_t = \sigma(W_o . |h_{t-1}, x_t| + b_o) \quad 7$$

The last output and the state decision vectors are multiplied to the tanh layer

$$h_t = O_t \tanh(C_t) \quad 8$$

3.3. The Hybrid Deep CNN+LSTM Model

The developed Hybrid Deep CNN+LSTM paradigm (HDCLN) for implant identification and classification combined CNN and LSTM to form a single network. The LSTM layer is placed before the FC layer of the conventional CNN to serve as the classifier. The Convolutional layers of the traditional CNN are employed to draw out complex features from the implant graphics and each pooling layer of the CNN down samples the output of the preceding layer to lessen the size of the parameters. The output of the last pooling layer is forwarded to the Long Short Term Memory layer for classification. The CNN based feature extraction has five blocks. Each CNN block comprise of two 2D Convolutional layers followed by one pooling layer. The LSTM classification layer consists of one LSTM layer, which is accompanied by a FC layer and one output layer.The developed system for identification and classification of shoulder implants is illustrated in Figure 3.

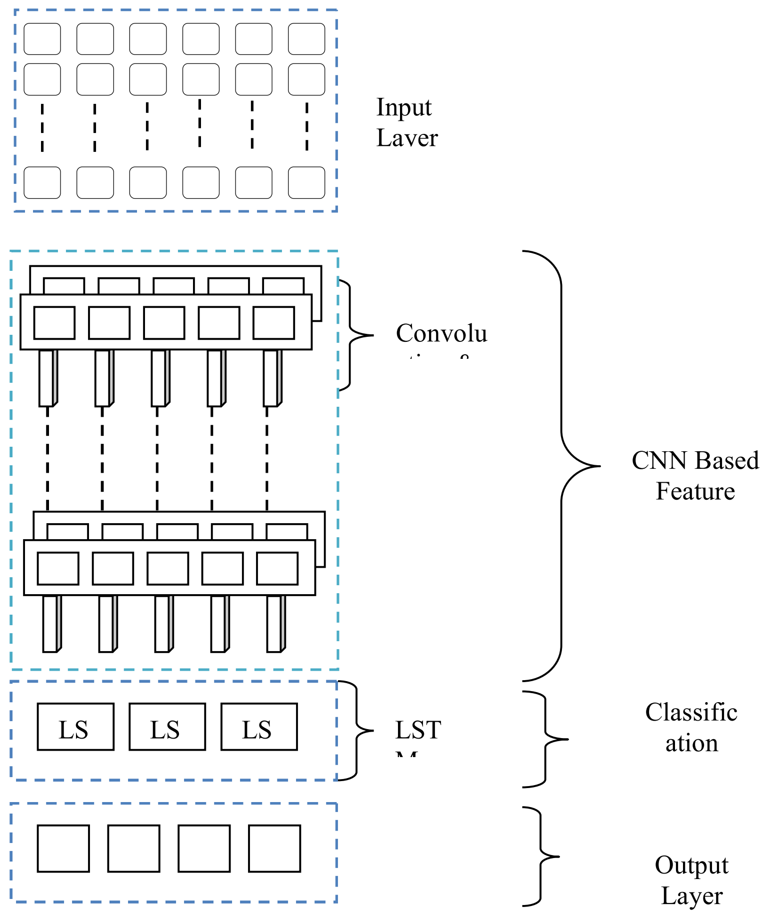

Fig. 4. Structure of HDCLN

The summary of the proposed deep hybrid CNN-LSTM network for implant identification and detection is presented in table 1.

Table 1. Layer Configuration of the developed hybrid system for implant identification and classification

Layer	Type of Layer	Filter size	Stride
Convolution	Conv2D	3 x 3	1
Convolution	Conv2D	3 x 3	1
Pooling	MaxPool	2 x 2	2
Convolution	Conv2D	3 x 3	1
Convolution	Conv2D	3 x 3	1
Pooling	MaxPool	2 x 2	2
Convolution	Conv2D	3 x 3	1
Convolution	Conv2D	3 x 3	1
Pooling	MaxPool	2 x 2	2

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Convolution	Conv2D	3 x 3	1
Convolution	Conv2D	3 x 3	1
Pooling	MaxPool	2 x 2	2
Convolution	Conv2D	3 x 3	1
Convolution	Conv2D	3 x 3	1
Pooling	MaxPool	2 x 2	2
LSTM	-	-	-
Fully Connected	-	-	-
Dense	-	-	-

3.4. Dataset

To test the proposed deep hybrid CNN-LSTM network, we collected the data used . The dataset was collected from different sources, which include prosthesis from BIDALlab in San Francisco State University, Common US shoulder prosthesis, various manufacturers' website, and Feeley Lab at University of California, San Francisco. The initial collection consists of 605 X-Ray images of 8-bit gray scale in jpeg format with varying dimensions. 8 images appeared to be collected from the same patients and were eliminated from the initial collection. The dataset contain images from four (4) different manufacturers as follows:

Cofield (83 images), Depuy (294), Tornier (71) and Zimmer (149). The class labels of the prosthesis are provided as the manufacturers names in the file names. The figure below shows some example of the X-Ray images of the prosthesis from the four manufacturers.

(a) Cofield

(b) Depuy

\

(c)Tornier (d) Zimmer

4. EXPERIMENT AND RESULTS

The proposed method was implemented using Python and TensorFlow (Keras) on Google Colab pro environment with high speed GPU, 12.69 GB of RAM and 166.83GB of Disk space. Due to the imbalance in number of images in the classes of the dataset, we expand the number of images in Cofield, Tornier and Zimmer class using data augmentation. We resize the images of the classes to spatial dimensions with resolution of 124 x 124 x 3. The dataset is randomly divided into 5 fold for a cross validation and the model was trained using RMS prop optimizer with an initial learning rate of 0.0001 with a batch size of 32 for 150 epoch. After the training, the model was tested on the holdout subset and the performance of the model was recorded.

4.1. EVALUATION METRICS

1. $$Accuracy = \frac{TP+TN}{TN+FP+TP+FN} \quad 9$$

2. $$Precision = \frac{TP}{TP+FP} \quad 10$$

3. $$Recal = \frac{TP}{TP+TN} \quad 11$$

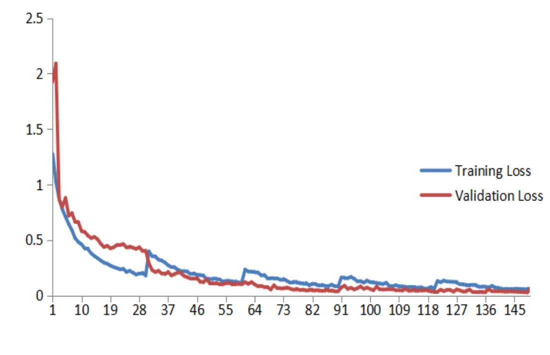
4. $$Recal = \frac{TP}{TP+TN} \quad 12$$

5. $$F1_{Score} = 2 * \frac{Precission*Recall}{Precission+Recall} \quad 13$$

(b) Depuy

4. 2. RESULT

(a) Accuracy



(b) Loss

Fig. 7. Evaluation metric of the developed hybrid deep CNN-LSTM paradigm for implant classification

Figure 7 shows the performance evaluation of the proposed hybrid deep CNN-LSTM network with training accuracy and loss and validation accuracy and loss. After training the model for 150 epochs, an overall training accuracy of 98% and validation accuracy of 99.2% was achieved. Also, the training and validation loss of the model after 150 epochs is 0.0561 and 0.0267 respectively.

Table 2. Performance of the hybrid deep CNN-LSTM network for implant classification

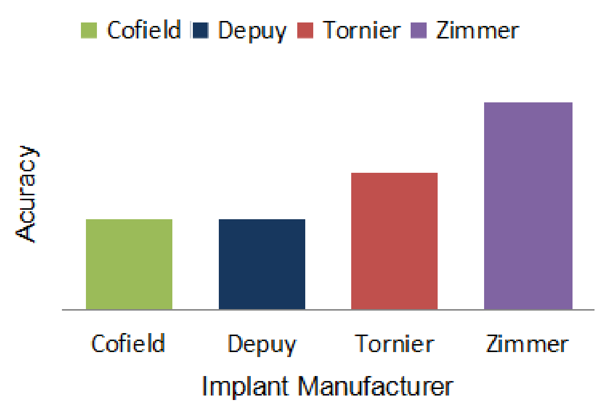
Class	Accuracy	F1_Score	Precision	Recall
Cofield	98	98	98	99
Depuy	98	98	97	97
Tornier	98.2	98	98	98
Zimmer	98.5	98	98	98

As can be seen from table 2, the developed hybrid system achieved 98% accuracy, 98% F1_score, 98% precision and 99% recall for the Cofield implants. For Depuy classification, the hybrid deep CNN-LSTM network achieved 98% accuracy and F1_score and 97% precision and 97% recall. In the Tornier implants, the proposed method obtained 98.2% accuracy, 98% F1_score, and 98% Precision and 98% recall as well. Also, the developed hybrid system achieves 98.5% accuracy and 98% F1_Score, 98% precision and 98% recall for Zimmer implant class.

Table 3. Performance comparison of state-of-the-art approach with the proposed hybrid deep CNN-LSTM network

Method	Accuracy	F1-Score	Precision	Recall
VGG-16	68.85	66.90	66.82	67.22
VGG-19	66.54	63.54	63.81	63.35
ResNet-50	80.57	78.02	79.21	76.95
NasNet	79.23	76.28	77.25	75.44
DenseNet	84.75	83.76	85.21	82.42
CNN	97	96.5	96	96.2
CNN-LSTM	98.7	98	98	98

Table 3 shows the comparison of performance of six deep learning approaches with the proposed hybrid deep CNN-LSTM network in terms of the mentioned evaluation metrics. Based on the results obtained in the experiments, the developed hybrid system outperforms the state-of-the-art approaches.



(a) Accuracy

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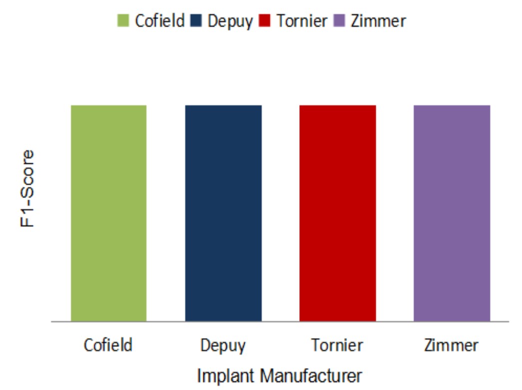
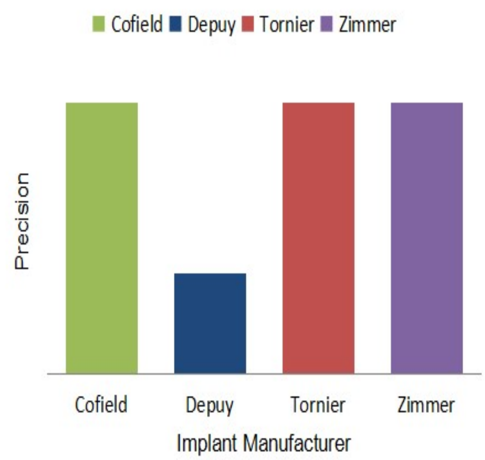
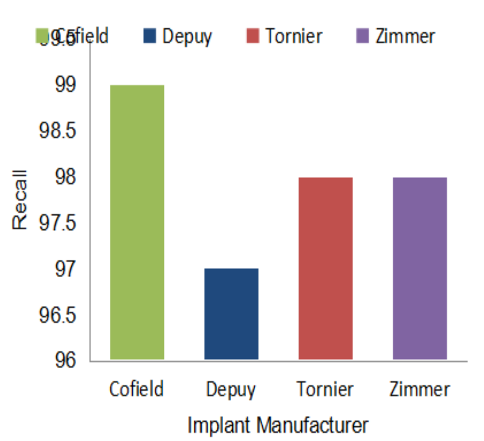


(b) F1-Score



(c) Precision



(D) Recall

Fig 8. Graphical Representation Of The Metrics Values

5. CONCLUSION

Artificial prosthesis has been widely used to mitigate and re-establish movement in human shoulder. This prosthesis usually requires services or replacement in future. Identification and classification of the implant manufacturer is the key step to successful surgery. To ensure prompt and error free surgery, there is need for a robust identification and classification system. In this study, we proposed a hybrid deep CNN-LSTM model for identification and classification of shoulder implants based on manufacturer. We used the CNN layer to extract features from the radiographic images and the LSTM layer for identification and classification of implants. Based on experimental results, the proposed model achieved the accuracy of 98.7%, precision of 98%, F1-score of 98.2% and recall of 98%. According to the performance of the model, we believe that this model will be a useful tool in preoperative planning and can be applied in the identification and classification of implants from other manufacturers. In future, we will test the generalizability of the model to classify all implants from different manufacturers when more dataset is available. Secondly, we will compare the performance of the proposed method with response from surgeon.

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