(12) PATENT APPLICATION PUBLICATION
(19) INDIA
(22) Date of filing of Application :29/04/2023

(21) Application No.202341030895 A
(43) Publication Date : 05/05/2023

(54) Title of the invention : A SYSTEM FOR ENSEMBLE LEARNING WITH CONVOLUTION NEURAL NETWORK FOR AUTOMATIC IDENTIFICATION OF IMPLANT MANUFACTURER USING X-RAY RADIOGRAPHS

(51) International classification	:A61B 060000, G06K 096200, G06N 030400, G06N 030800, G06N 202000
(86) International Application No Filing Date	:PCT// :01/01/1900
(87) International Publication No	: NA
(61) Patent of Addition to Application Number Filing Date	:NA :NA
(62) Divisional to Application Number Filing Date	:NA :NA

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(57) Abstract :
[038] The present invention discloses a system for ensemble learning with Convolution Neural Network for automatic identification of implant manufacturer using X-ray radiographs. In the present invention, an ensemble model for automatic implant manufacturer prediction using X-ray radiography. Our model employs multiple convolutional neural networks to achieve a reliable prediction of the implant manufacturer based on x-ray images. The individual CNN varients involved in the implant prediction were trained separately to make independent predictions and then combined using a weighted average ensembling method to predict the manufacturer of the implant. We trained the individual pre-trained model for 150 epochs using the training set and validated the model using the validation set. The performance of the pretrained models were monitored and evaluated based on model accuracy, precision, recall and F1 score. The ensemble model has shown promising performance in terms of the aforementioned evaluation metrics, thus we believe that the model will be a useful tool in preoperative planning and can be applied in the identification and classification of implants from other manufacturers. Accompanied Drawing [FIGS. 1-2]

No. of Pages : 26 No. of Claims : 7

“**FORM 1** THE PATENTS ACT 1970 (39 of 1970) and THE PATENTS RULES, 2003 **APPLICATION FOR GRANT OF PATENT** (See section 7, 54 and 135 and sub-rule (1) of rule 20)	(FOR OFFICE USE ONLY)

	Application No.	
	Filing date:	
	Amount of Fee paid:	
	CBR No:	
	Signature:	
1. APPLICANT’S REFERENCE / IDENTIFICATION NO. (AS ALLOTTED BY OFFICE)		

2. TYPE OF APPLICATION [Please tick (✓) at the appropriate category]

Ordinary (✓)		Convention ( )		PCT-NP ( )	
Divisional ( )	Patent of Addition ( )	Divisional ( )	Patent of Addition ( )	Divisional ( )	Patent of Addition ( )

3A. APPLICANT(S)

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3B. CATEGORY OF APPLICANT [Please tick (✓) at the appropriate category]

Natural Person ()	Other than Natural Person		
	Small Entity ( )	Startup ()	Others (✓)

4. INVENTOR(S) [Please tick (✓) at the appropriate category]

Are all the inventor(s) same as the applicant(s) named above?	Yes ()	No (✓)

If “No”, furnish the details of the inventor(s)

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5. TITLE OF THE INVENTION

"A SYSTEM FOR ENSEMBLE LEARNING WITH CONVOLUTION NEURAL NETWORK FOR AUTOMATIC IDENTIFICATION OF IMPLANT MANUFACTURER USING X-RAY RADIOGRAPHS"

6. AUTHORISED REGISTERED PATENT AGENT(S)	IN/PA No.	
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~~8. IN CASE OF APPLICATION CLAIMING PRIORITY OF APPLICATION FILED IN CONVENTION COUNTRY, PARTICULARS OF CONVENTION APPLICATION~~

~~Country~~	~~Application Number~~	~~Filing date~~	~~Name of the applicant~~	~~Title of the invention~~	~~IPC (as classified in the convention country)~~

~~9. IN CASE OF PCT NATIONAL PHASE APPLICATION, PARTICULARS OF INTERNATIONAL APPLICATION FILED UNDER PATENT CO-OPERATION TREATY (PCT)~~

~~International application number~~	~~International filing date~~

~~**10. IN CASE OF DIVISIONAL APPLICATION FILED UNDER SECTION 16, PARTICULARS OF ORIGINAL (FIRST) APPLICATION**~~	
~~Original (first) application No.~~	~~Date of filing of original (first) application~~
~~**11. IN CASE OF PATENT OF ADDITION FILED UNDER SECTION 54, PARTICULARS OF MAIN APPLICATION OR PATENT**~~	
~~Main application/patent No.~~	~~Date of filing of main application~~
12. DECLARATIONS	

i) Declaration by the inventor(s)

(**In case the applicant is an assignee**: the inventor(s) may sign herein below or the applicant may upload the assignment or enclose the assignment with this application for patent or send the assignment by post/electronic transmission duly authenticated within the prescribed period).

I/We, the above named inventor(s) is/are the true & first inventor(s) for this Invention and declare that the applicant(s) herein is/are my/our assignee or legal representative.

(a) Date 29/04/2023

(b) Name	(c) Signature
1. Prof. James Stephen Meka 2. Mr.Rajendraprasad Banavathu 3. Prof. Prasad Reddy P.V.G.D.	

~~**(ii) Declaration by the applicant(s) in the convention country**~~

~~**(In case the applicant in India is different than the applicant in the convention country:** the applicant in the convention country may sign herein below or applicant in India may upload the assignment from the applicant in the convention country or enclose the said assignment with this application for patent or send the assignment by post/electronic transmission duly authenticated within the prescribed period)~~

~~I/We, the applicant(s) in the convention country declare that the applicant(s) herein is/are my/our assignee or legal representative.~~

~~(a) Date~~

~~(b) Signature(s)~~

(c) ~~Name(s) of the signatory~~

(iii) Declaration by the applicant(s)

I/We the applicant(s) hereby declare(s) that: -

- ~~I am/~~ We are in possession of the above-mentioned invention.
- The ~~provisional~~/complete specification relating to the invention is filed with this application.
- ~~The invention as disclosed in the specification uses the biological material from India and the necessary permission from the competent authority shall be submitted by me/us before the grant of patent to me/us.~~
- There is no lawful ground of objection(s) to the grant of the Patent to me/us.
- ~~I am~~/we are the true & first inventor(s).
- ~~I am/we are the assignee or legal representative of true & first inventor(s).~~
- ~~The application or each of the applications, particulars of which are given in Paragraph-8, was the first application in convention country/countries in respect of my/our invention(s).~~
- ~~I/We claim the priority from the above mentioned application(s) filed in convention country/countries and state that no application for protection in respect of the invention had been made in a convention country before that date by me/us or by any person from which I/We derive the title.~~
- ~~My/our application in India is based on international application under Patent Cooperation Treaty (PCT) as mentioned in Paragraph-9.~~
- ~~The application is divided out of my /our application particulars of which is given in Paragraph-10 and pray that this application may be treated as deemed to have been filed on DD/MM/YYYY under section 16 of the Act.~~
- ~~The said invention is an improvement in or modification of the invention particulars of which are given in Paragraph-11.~~

13. FOLLOWING ARE THE ATTACHMENTS WITH THE APPLICATION

(a) Form 2

Item	Details	Fee	Remarks
Complete/ ~~Provisional~~ specification) #	No. of pages: 18		
No. of Claim(s)	No. of claims: 07 No. of pages: 02		
Abstract	No. of pages: 01		
No. of Drawing(s)	No. of drawings: 13 No. of pages: 05		

In case of a complete specification, if the applicant desires to adopt the drawings filed with his provisional specification as the drawings or part of the drawings for the complete specification under rule 13(4), the number of such pages filed with the provisional specification are required to be mentioned here.

(b) Complete specification (in conformation with the international application)/as amended before the International Preliminary Examination Authority (IPEA), as applicable (2 copies).

(c) Sequence listing in electronic form

(d) Drawings (in conformation with the international application)/as amended before the International Preliminary Examination Authority (IPEA), as applicable (2 copies).

(e) Priority document(s) or a request to retrieve the priority document(s) from DAS (Digital Access Service) if the applicant had already requested the office of first filing to make the priority document(s) available to DAS.

(f) Translation of priority document/Specification/International Search Report/International Preliminary Report on Patentability.

(g) Statement and Undertaking on Form 3

(h) Declaration of Inventorship on Form 5

(i)Power of Authority

(j)**Total fee ₹……….in Cash/ Banker's Cheque /Bank Draft bearing No.......... Date on …………. Bank.**

I/We hereby declare that to the best of my/our knowledge, information and belief the fact and matters slated herein are correct and I/We request that a patent may be granted to me/us for the said invention.

Dated this 29th day of April 2023

Applicant: Dr. B. R. Ambedkar Chair-Andhra University

To,

The Controller of Patents

The Patent Office, at Chennai

Note: -

* Repeat boxes in case of more than one entry.
* To be signed by the applicant(s) or by authorized registered patent agent otherwise where mentioned.
* Tick ()/cross (x) whichever is applicable/not applicable in declaration in paragraph-12.
* Name of the inventor and applicant should be given in full, family name in the beginning.
* Strike out the portion which is/are not applicable.
* For fee: See First Schedule";

FORM 2

THE PATENTS ACT, 1970

(39 of 1970)

&

The Patent Rules, 2003

COMPLETE SPECIFICATION

(See section 10 and rule 13)

TITLE OF THE INVENTION

"A SYSTEM FOR ENSEMBLE LEARNING WITH CONVOLUTION NEURAL NETWORK FOR AUTOMATIC IDENTIFICATION OF IMPLANT MANUFACTURER USING X-RAY RADIOGRAPHS"

Applicant:

Dr. B. R. Ambedkar Chair-Andhra University,

Andhra University, Visakhapatnam, Andhra Pradesh, India. Pin Code:530003.

The following specification particularly describes the nature of the invention and the manner in which it is performed:

FIELD OF THE INVENTION

[001] The present invention relates to the field of the system system for ensemble learning with Convolution Neural Network with novel techniques, methods, devices and apparatus. The invention more particularly relates to a system for ensemble learning with Convolution Neural Network for automatic identification of implant manufacturer using X-ray radiographs.

BACKGROUND OF THE INVENTION

[002] The following description provides the information that may be useful in understanding the present invention. It is not an admission that any of the information provided herein is prior art or relevant to the presently claimed invention, or that any publication specifically or implicitly referenced is prior art.

[003] Further, the approaches described in this section are approaches that could be pursued, but not necessarily approaches that have been previously conceived or pursued. Therefore, unless otherwise indicated, it should not be assumed that any of the approaches described in this section qualify as prior art merely by virtue of their inclusion in this section.

[004] To replace the damaged ball and sockets in the human shoulder, prostheses made of polyethelene and metallic components are frequently used nowadays. Due to degradation in the quality of the prosthesis, reoperation and revision may be required years after the replacement. Information on the prototype and the relevant prosthesis maker are needed for this step. In some cases, the patient and the primary physician may be unaware of the prosthesis' prototype and maker. Typically, manual identification of the prosthesis' prototype and maker is done during preoperative planning. The manual identification of the model and manufacturer, however, takes time and is error prone. An automatic model identification and manufacturer classification system can speed up the treatment process and reduce the operation risk associated with the manual model identification system. In this paper, an ensemble model based on multiple benchmarks for convolution neural networks is proposed. The ensemble model combined three pre-trained CNN models (DenseNet201, ResNet50, and MobileNetV2) to provide a reliable conclusion on the implant manufacturer during the revision process. The individual pre-trained models are trained separately to make independent predictions and then finally combined using an average weighted ensemble technique to form the ensemble model. 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 a dataset to train and test the model. Experimental results show that the ensemble model performs better than the individual pre-trained models. 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.

[005] In order to treat injured shoulder joints, total shoulder arthroplasty is frequently used. Common causes of shoulder damage and dysfunction include trauma, deposition, weakening of the shoulder cartilage tissue, harm to surrounding bones, and severe arthritis. The shoulder will malfunction as a result of this damage and suffer severe trauma. When the damage to the shoulder joint is severe, surgery may be used to relieve pain and restore motion to the patient's shoulder. The injured joint is separated and substituted with a synthetic prosthetic joint during the TSA surgery. The correctness of the synthetic prosthesis' positioning after surgery is assessed using X-ray implant images, which are used to assess the prosthesis' suitability before operation. Several shoulder prosthesis manufacturers presently produce a variety of variants of this prosthesis to suit a range of patients and circumstances. When the performance of the prosthesis deteriorates years after the transplant, reoperation and correction may be necessary. Identification of the model, anatomy, and manufacturer of the prosthesis is a key surgical step to reduce the typical difficulties and place them in the right position. When a patient relocates from the place or nation where they had surgery, it's possible that both they and their primary doctor in the new place or country are uninformed of the prosthesis' model and maker. Therefore, to determine the type of the prosthesis and the manufacturer, a thorough inspection and ocular comparison of radiographic images are needed. This method takes a lot of time, is error-prone, and causes delays in reoperation and modification.

[006] Numerous researchers have proven several deep learning algorithms to categorise implants based on their manufacturer and determine their model and design. To automatically identify implant manufacturers, deep learning techniques such as ResNet, Convolutional Neural Network (CNN), Neural Network, VGG, GoogleNet, and Inception have been applied recently. These techniques have been used as feature extractors to improve the accuracy of implant identification and classification. To ensure a high level of accuracy and reliability in the prediction of implant manufacturer, there is a need for a more robust approach that can guarantee a high level of reliability in the choice of implant to use during the revision process.

[007] In a real-life scenario, medical diagnoses based on multiple medical expert views are more accurate and preferable. The combination of multiple medical experts aids in achieving a more reliable conclusion. Using the same philosophy, this paper proposed an ensemble model for automatic implant manufacturer prediction using X-ray radiography. The proposed ensemble model employs multiple convolutional neural networks to achieve a reliable prediction of the implant manufacturer based on x-ray images. The individual models involved in the implant prediction have been trained separately to make independent predictions. The trained models are combined using a weighted average ensembling method to predict the manufacturer of the implant.

[008] The main contributions of this paper are summarized as follows:

To develop a deep learning-based model for automatic implant manufacturer prediction using X-ray radiographs;

To develop an ensemble model that provides reliable conclusion based on the outcome of multiple individual pre-trained models; and

To prove the ability of ensemble models to yield better performance than the individual learning models.

[009] Accordingly, on the basis of aforesaid facts, there remains a need in the prior art to provide a system for ensemble learning with Convolution Neural Network for automatic identification of implant manufacturer using X-ray radiographs. Therefore, it would be useful and desirable to have a system, method, apparatus and interfaces to meet the above-mentioned needs.

SUMMARY OF THE PRESENT INVENTION

[010] In view of the foregoing disadvantages inherent in the known types of conventional analysis systems, methods and techniques, are now present in the prior art, the present invention provides a system for ensemble learning with Convolution Neural Network for automatic identification of implant manufacturer using X-ray radiographs, which has all the advantages of the prior art and none of the disadvantages.

[011] It is an object of the present invention and the need for identification of implant manufacturer is the initial and crucial step for revision to re-establish movement and mitigate pain in an operated shoulder. To make a reliable conclusion on the manufacturer, there is need for a rigorous examination and visual comparison of radiographic images of various implant manufacturers. This approach is liable to errors that can significantly affect the entire revision process and prolong the time and suffering by the victim. To address these issues, we proposed an ensemble model for automatic implant manufacturer prediction using X-ray radiography. Our model employs multiple convolutional neural networks to achieve a reliable prediction of the implant manufacturer based on x-ray images. The individual CNN varients involved in the implant prediction were trained separately to make independent predictions and then combined using a weighted average ensembling method to predict the manufacturer of the implant. We trained the individual pre-trained model for 150 epochs using the training set and validated the model using the validation set. The performance of the pretrained models were monitored and evaluated based on model accuracy, precision, recall and F1 score.

[012] Furthermore, the ensemble model has shown promising performance in terms of the aforementioned evaluation metrics, thus we believe that the 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 compare the result of our model with the conclusions made by multiple physicians.

[013] In this respect, before explaining at least one object of the invention in detail, it is to be understood that the invention is not limited in its application to the details of set of rules and to the arrangements of the various models set forth in the following description or illustrated in the drawings. The invention is capable of other objects and of being practiced and carried out in various ways, according to the need of that industry. Also, it is to be understood that the phraseology and terminology employed herein are for the purpose of description and should not be regarded as limiting.

[014] These together with other objects of the invention, along with the various features of novelty which characterize the invention, are pointed out with particularity in the disclosure. For a better understanding of the invention, its operating advantages and the specific objects attained by its uses, reference should be made to the accompanying drawings and descriptive matter in which there are illustrated preferred embodiments of the invention.

BRIEF DESCRIPTION OF THE DRAWINGS

[015] When considering the following thorough explanation of the present invention, it will be easier to understand it and other objects than those mentioned above will become evident. Such description refers to the illustrations in the annex, wherein:

[016] FIGS. 1-13, illustrate various representations for a system for ensemble learning with Convolution Neural Network for automatic identification of implant manufacturer using X-ray radiographs, in accordance with an embodiment of the present invention.

DETAILED DESCRIPTION OF THE INVENTION

[017] The following sections of this article will provide various embodiments of the current invention with references to the accompanying drawings, whereby the reference numbers utilised in the picture correspond to like elements throughout the description. However, this invention is not limited to the embodiment described here and may be embodied in several other ways. Instead, the embodiment is included to ensure that this disclosure is extensive and complete and that individuals of ordinary skill in the art are properly informed of the extent of the invention. Numerical values and ranges are given for many parts of the implementations discussed in the following thorough discussion. These numbers and ranges are merely to be used as examples and are not meant to restrict the claims' applicability. A variety of materials are also recognised as fitting for certain aspects of the implementations. These materials should only be used as examples and are not meant to restrict the application of the innovation.

[018] Referring now to the drawings, these are illustrated in FIGS. 1-13, the present invention discloses a system for ensemble learning with Convolution Neural Network for automatic identification of implant manufacturer using X-ray radiographs.

[019] In accordance with another embodiment of the present invention, the structure and the working process of the pre-trained models (DenseNet201, ResNet50, and MobileNetV2) adopted in the ensemble model are explained.

ResNet

[020] In accordance with another embodiment of the present invention, ResNet, also known as residual network, is an Artificial Neural Network (ANN) that uses skip connections or shortcuts to build a deeper ANN by skipping some neuron layers. The various versions of ResNet include ResNet-18, ResNet-34, ResNet-50, and so on, where the numbers represent the number of layers present in the model. A residual block of ResNet architecture is created by adding a shortcut to the main part of the plain neural network. A residual block is an identity block when the input and output activation dimensions are similar and a convolution block otherwise. The stacking of residual blocks forms the residual network. Figure 1 below shows the residual blocks of the ResNet architecture.

DenseNet

[021] In accordance with another embodiment of the present invention, DenseNet is a variant of Neural Network that is used for visual object recognition. DenseNet concatenates the output of the preceding layer with the future layers. It was developed to enhance the decline in accuracy caused by the vanishing gradient in advanced level NN.

MobileNet

[022] In accordance with another embodiment of the present invention, convolutional neural networks, such as MobileNet, are specialised for use in embedded and mobile vision applications. They are built using depthwise separable convolutions, which are lightweight deep neural networks that can have minimal latency for embedded and mobile devices.

<u>Best Mode & Enablement of the present invention</u>

[023] In accordance with another embodiment of the present invention, the proposed approach in this work employs multiple convolutional neural networks to achieve a reliable prediction of implant manufacturer based on x-ray images. The individual models involved in the implant prediction have been trained separately to make independent predictions. The trained models are combined using a weighted average ensembling method to predict the manufacturer of the implant. The ensemble model is made up of the previously mentioned models: DenseNet201, ResNet50, and MobileNetV2. The phases involved in the proposed automatic implant prediction approach are depicted in figure 4.

Data Collection

[024] In accordance with another embodiment of the present invention, to evaluate the performance of the ensemble model, the dataset was collected from different sources, which include prosthesis from BIDAL lab 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.

Data Preprocessing

[025] In accordance with another embodiment of the present invention, in this phase, the dataset is segregated into four classes based on the manufactures of the implant with each class labeled as the name of the manufacturer. The image data were resized to a uniform size of 124x124 and then normalized to resolve the variation in resolution of the implant X-ray graphics. To avoid any element of bias in splitting the dataset and improve the quality and performance of the model, we shuffled the dataset prior to data splitting.

Data Partitioning

[026] In accordance with another embodiment of the present invention, the preprocessed data from the preprocessing pipeline is partitioned into training set, testing set and validation set. The training set comprises of 60% of the overall dataset and the testing and validation dataset each contains 20% of the overall dataset. The training dataset is used to train the model and the validation and test dataset is used to validate the model and test the performance of the model

Model Development and Training

[027] In accordance with another embodiment of the present invention, in this phase, the pre-trained models (DenseNet201, ResNet50 and MobileNetV2) are developed and trained using the training dataset. The corresponding training accuracy and training loss of the individual pre-trained model were monitored. Also, the conventional 5-fold cross validation approach is employed in validating the individual pre-trained model and the corresponding validation accuracy and validation loss were monitored.

Ensemble Model

[028] In accordance with another embodiment of the present invention, the ensemble model is developed by combining the pre-trained models using a weighted average ensembling method to predict the manufacturer of implant. The weight of the models are assigned in such a way that, the model with lower validation error is assigned a higher weight so that it's contribution in deciding the implant manufacturer is higher. Given a_i as the percentage accuracy of i^{th} model, the validation loss of the i^{th} model is calculated as follows:

$$vl = 100 - ai \qquad 1$$

And the weight of the ith model is calculated as follows:

$$w_i = \frac{vl}{\sum_{k=1}^{n} vl_k} \qquad 2$$

Where n is the number of pre-trained model used

Performance Evaluation

[029] In accordance with another embodiment of the present invention, in this phase, the performance of the individual pre-trained model and the ensemble model are checked. The performance of the model is evaluated by computing the accuracy, precision, recall, F1-score and confusion matrix. The performance metrics used are expressed as follows:

$$Accuracy = \frac{TP+TN}{TN+FP+TP+FN} \qquad 3$$

$$Precision = \frac{TP}{TP+FP} \quad 4$$

$$Recal = \frac{TP}{TP+TN} \quad 5$$

$$F1_{Score} = 2 * \frac{Precission*Recall}{Precission+Recall} \quad 6$$

Where TP represent true positive, TN represents true negative, FP represents false positive and FN represents false negative

Model Comparison

[030] In accordance with another embodiment of the present invention, in this phase, the three pre-trained models and the ensemble model are compared based on their performance in correctly predicting the manufacturer of the implants.

Experiment and Results

[031] In accordance with another embodiment of the present invention, the pre-trained models and the ensemble model were implemented using Colab GPU (Tesla K80 12GB GDDR5 VRAM), Python 3.9 and TensorFlow 2.2.0. 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 for 150 epoch. After the training, the model was tested on the holdout subset and the

[032] In accordance with another embodiment of the present invention, Figure 6 through 8 shows the learning curve for DenseNet201, ResNet50 and MobileNetV2 respectively. The figures present the training accuracy and validation accuracy and training loss and validation loss of the three pre-trained models. The models were trained for 150 epochs each, thus the figures presents the accuracies and losses for the models for each epoch. Based on the figures, it can be observed that the training accuracies and validation accuracies and training losses and validation losses closely increases and decreases for each model. This indicates that the models are well fit and can be generalized on an unseen implant radiograph.

[033] In accordance with another embodiment of the present invention, based on the reports presented in the table, DenseNet201 achieve the best performance in terms of accuracy, precision, recall and F1-score as compared to the ResNet50 and MobileNetV2. The MobileNetV2 model yield lower performance in terms of the evaluation metrics as the ResNet50 model.

Figure 9 through 12 shows the confusion matrices of the three pre-trained model and the ensemble model. Based on the figures, MobileNetV2 recorded the highest misclassifications with a total of 24 images from Cofield, misclassified as Zimmer and Depuy, 29 images from Depuy misclassified as Cofield and Tornier, a total of 3 images from Tornier misclassified as Depuy and a total of 22 images from Zimmer misclassified as Cofield. DenseNet201 and ResNet50 have performed well in the classification of implants based on manufacturer with a ceiling of 7 images misclassified by ResNet50. Based on figure 12, the ensemble model obtained by combining the three pre-trained model have correctly classified all the implants. With this performance, it can be concluded that the prediction of implant manufacture by the ensemble model can be highly reliable.

[034] In accordance with another embodiment of the present invention, table 5 shows the performance comparison of the three pre-trained models and the ensemble model. The corresponding performance is graphically represented in figure 13 above. Based on the comparison it can be seen that ensemble model achieve the best performance as compared to the individual pre-trained models. DenseNet201 and ResNet50 achieve a better performance as compared to MobileNetV2 pre-trained model. This shows that, DenseNet201 and ResNet50 have greater weight compared to the MobileNetV2, thus contribute more to determining the class of an implant.

[035] The above-mentioned invention is provided with the preciseness in its real-world applications to provide a a system for ensemble learning with Convolution Neural Network for automatic identification of implant manufacturer using X-ray radiographs.

[036] The benefits and advantages that the present invention may offer have been discussed above with reference to particular embodiments. These benefits and advantages are not to be interpreted as critical, necessary, or essential features of any or all of the embodiments, nor are they to be read as any elements or constraints that might contribute to their occurring or becoming more evident.

[037] Although specific embodiments have been used to describe the current invention, it should be recognized that these embodiments are merely illustrative and that the invention is not limited to them. The aforementioned embodiments are open to numerous alterations, additions, and improvements. These adaptations, changes, additions, and enhancements are considered to be within the purview of the invention.

We Claim:

1. An ensemble model for automatic implant manufacturer prediction using X-ray radiography, comprising:

   a plurality of convolutional neural network (CNN) variants, each trained independently to predict the manufacturer of an implant based on an X-ray image, wherein the CNN variants employ pre-trained models;

   a weighted average ensembling method configured to combine the independent predictions of the CNN variants and produce an ensemble prediction of the implant manufacturer;

   a training set and a validation set used to train and validate the CNN variants, respectively;

   a performance evaluation method based on accuracy, precision, recall, and F1 score used to monitor and evaluate the performance of the CNN variants during training and validation;

   wherein the ensemble model achieves a reliable prediction of the implant manufacturer based on X-ray images and can be applied in the identification and classification of implants from other manufacturers, thereby providing a useful tool in preoperative planning.

2. The ensemble model as claimed in claim 1, wherein each CNN variant is trained for 150 epochs using the training set.

3. The ensemble model as claimed in claim 1 or 2, wherein the X-ray radiography comprises a digital radiograph or a computed tomography (CT) scan.

4. The ensemble model of any of claims 1 to 3, wherein the ensemble prediction of the implant manufacturer is a probability distribution over a set of possible manufacturers.

5. The ensemble model of any of claims 1 to 4, wherein the performance evaluation method further comprises a confusion matrix analysis.

6. A computer-implemented method for predicting the manufacturer of an implant based on an X-ray image, comprising:

receiving an X-ray image of the implant;

applying the ensemble model of any of claims 1 to 5 to the X-ray image;

outputting an ensemble prediction of the implant manufacturer.

7. A computer-readable storage medium having instructions stored thereon that, when executed by a computing device, cause the computing device to perform the method of claim 6.

Dated this 29th day of April 2023

Applicant

Dr. B. R. Ambedkar Chair-Andhra University

ABSTRACT

A SYSTEM FOR ENSEMBLE LEARNING WITH CONVOLUTION NEURAL NETWORK FOR AUTOMATIC IDENTIFICATION OF IMPLANT MANUFACTURER USING X-RAY RADIOGRAPHS

[038] The present invention discloses a system for ensemble learning with Convolution Neural Network for automatic identification of implant manufacturer using X-ray radiographs. In the present invention, an ensemble model for automatic implant manufacturer prediction using X-ray radiography. Our model employs multiple convolutional neural networks to achieve a reliable prediction of the implant manufacturer based on x-ray images. The individual CNN varients involved in the implant prediction were trained separately to make independent predictions and then combined using a weighted average ensembling method to predict the manufacturer of the implant. We trained the individual pre-trained model for 150 epochs using the training set and validated the model using the validation set. The performance of the pretrained models were monitored and evaluated based on model accuracy, precision, recall and F1 score. The ensemble model has shown promising performance in terms of the aforementioned evaluation metrics, thus we believe that the model will be a useful tool in preoperative planning and can be applied in the identification and classification of implants from other manufacturers.

Accompanied Drawing **[FIGS. 1-2]**

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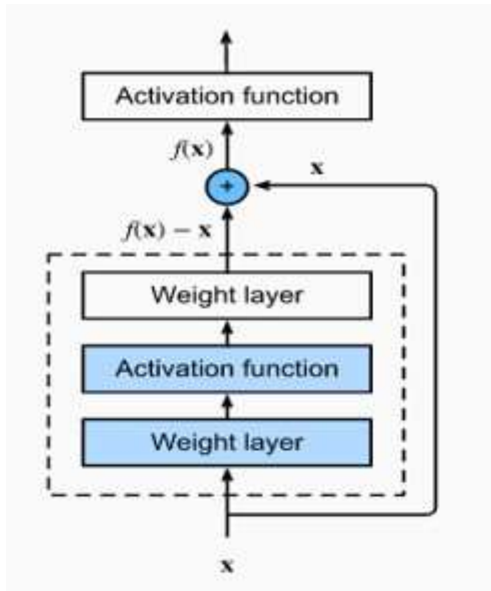


Figure 1 Residual Block [27]

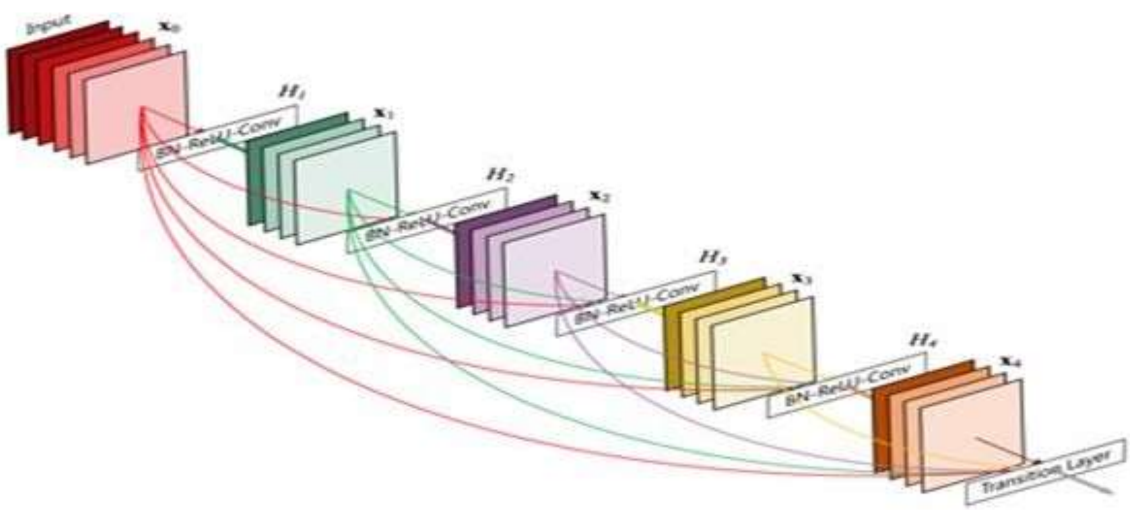


Figure 2 DenseNet Architecture [29]

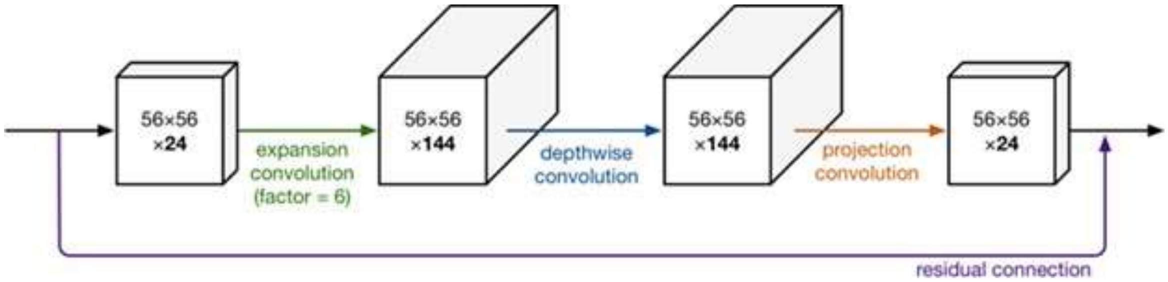


Figure 3 MobileNetV2 Architecture [30]

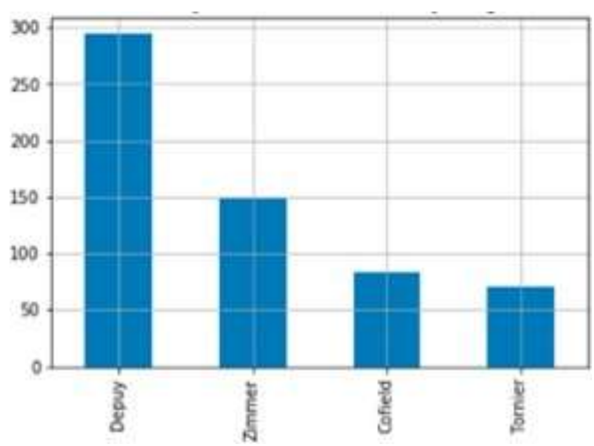


Figure 4 Comparison of Dataset Sizes of the four Major Classes

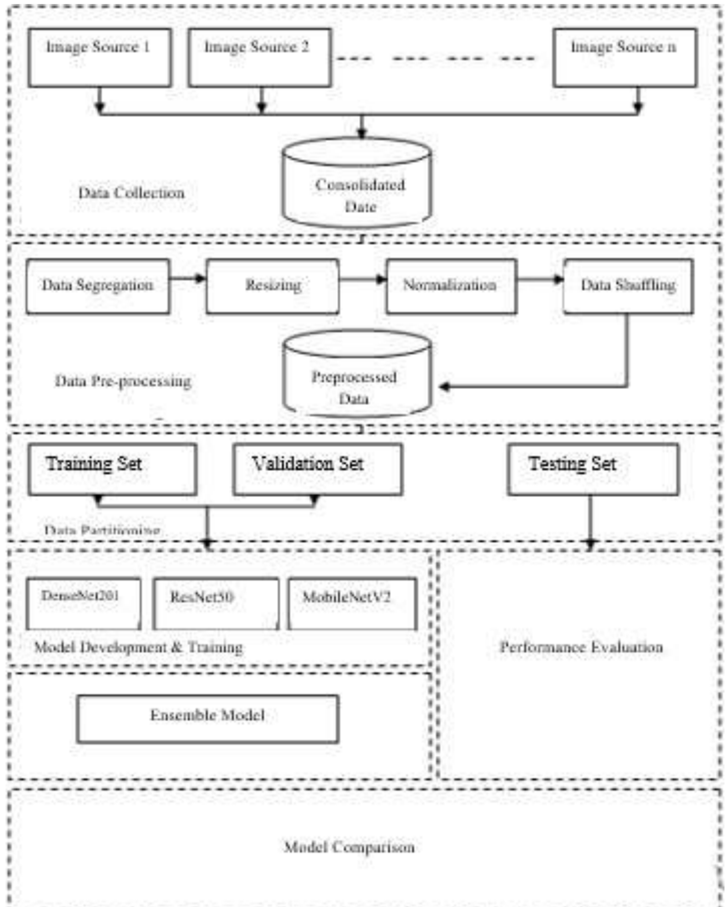


Figure 5 Architecture of the Proposed Implant Detection System

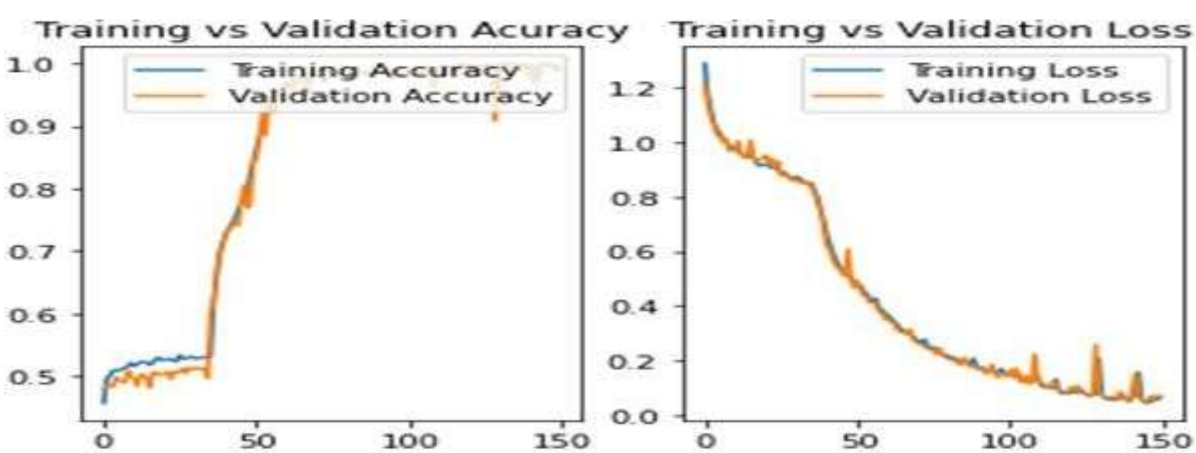


Figure 6 Training and Validation Accuracy for DenseNet201 Model

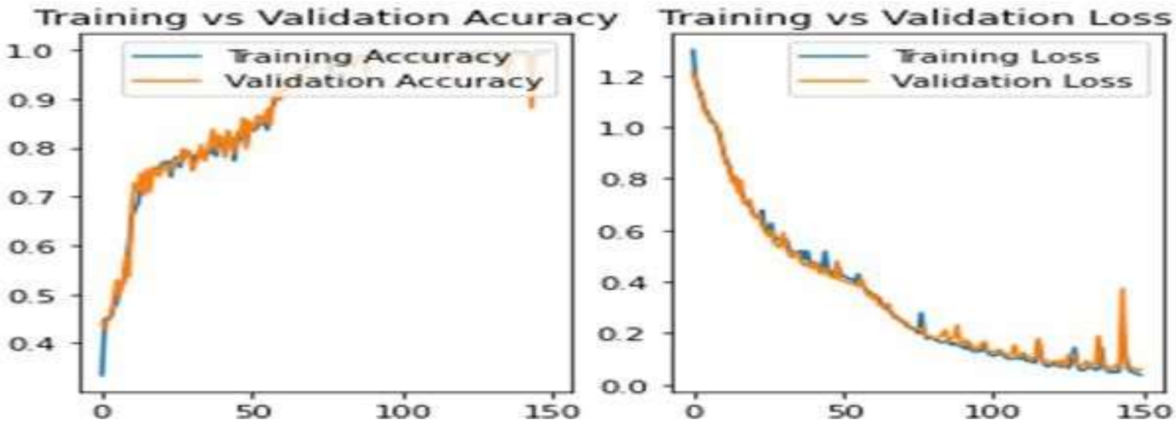


Figure 7 Training and Validation Accuracy for ResNet50

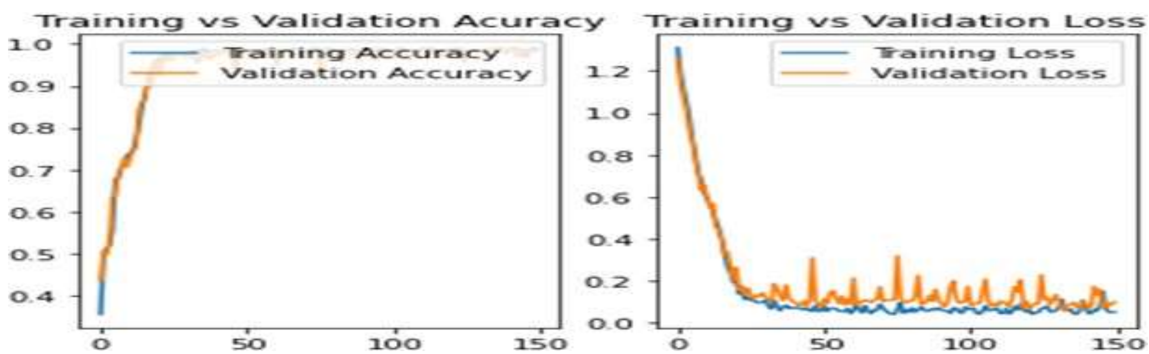


Figure 8 Training and Validation loss for MobileNetV2

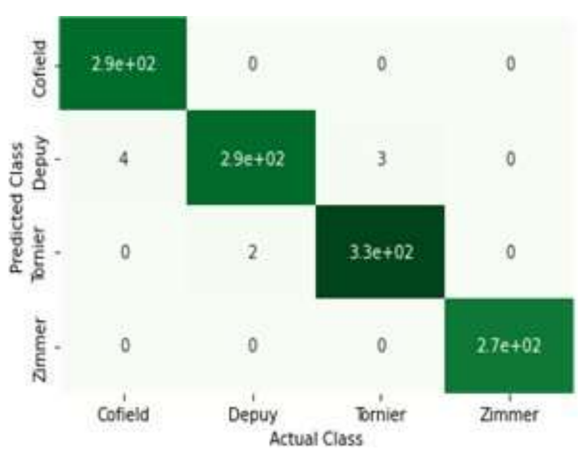
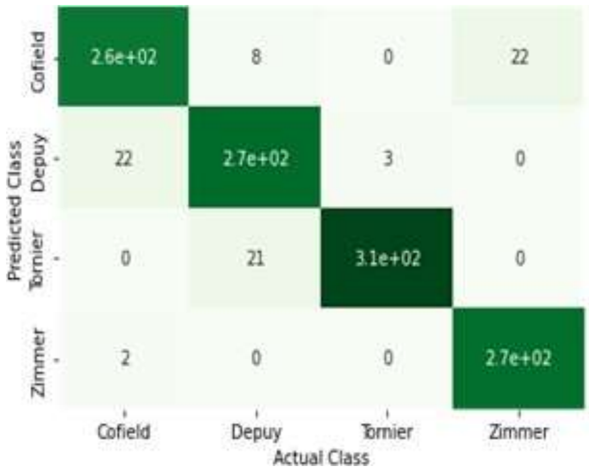


Figure 9 Confusion Matrix for DenseNet201

Figure 10 Confusion Matrix for ResNet50



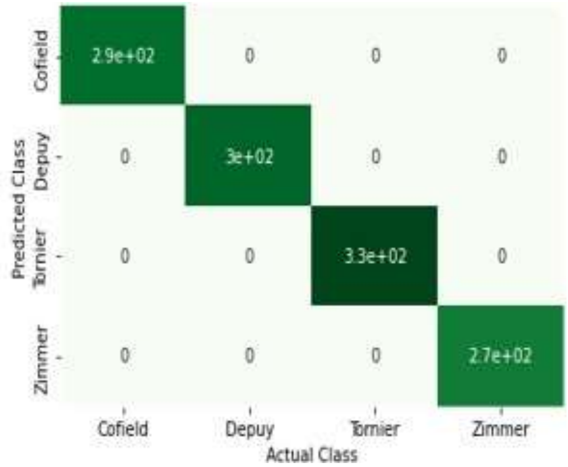


Figure 11 Confusion Matrix for MobileNetV2 Figure 12 Confusion Matrix for Ensemble Model

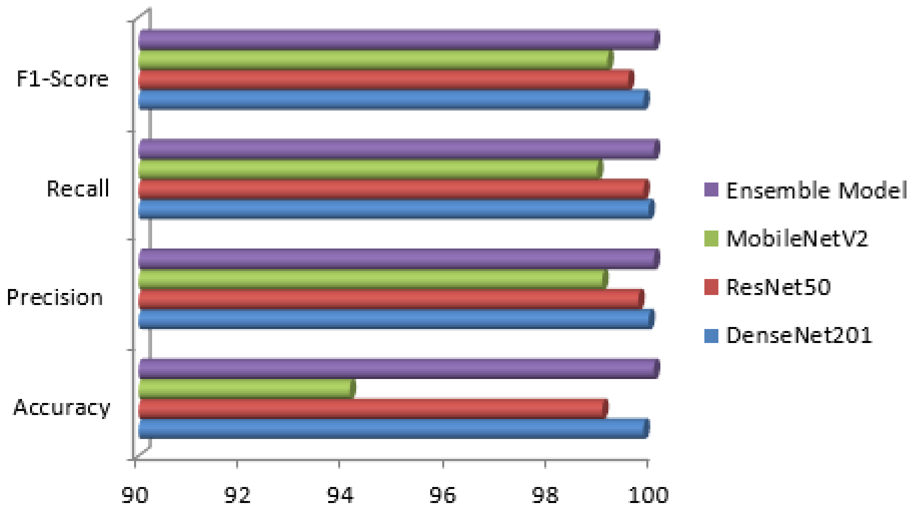


Figure 13 Performance of the pre-trained models and the Ensemble Model

Dataset	Cofield	Depuy	Tornier	Zimmer
Training	51	176	43	89
Validation	16	59	14	30
Testing	16	59	14	30

Table 1. Data distribution for training, validation and testing

Class	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Cofield	99.7	99	100	99
Depuy	99.4	99	98	98
Tornier	99.4	99	99	99
Zimmer	99.6	100	100	100

Table 2 Classification report for DenseNet201

Class	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Cofield	98.5	97	98	97
Depuy	98.0	100	99	98
Tornier	98.5	97	99	98
Zimmer	98.6	100	99	99

Table 3 Classification report for ResNet50

Class	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Cofield	93.9	99	100	99
Depuy	93.5	99	98	98
Tornier	93.8	99	99	99
Zimmer	93.9	100	100	100

Table 4 Classification report for MobileNetV2

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
DenseNet201	99.8	99.9	99.9	99.8
ResNet50	99	99.7	99.8	99.5
MobileNetV2	94.1	99	98.9	99.1
Ensemble Model	100	100	100	100

Table 5 Performance Comparison of DenseNet201, ResNet50, MobileNetV2 and Ensemble Model

Dated this 29th day of April 2023