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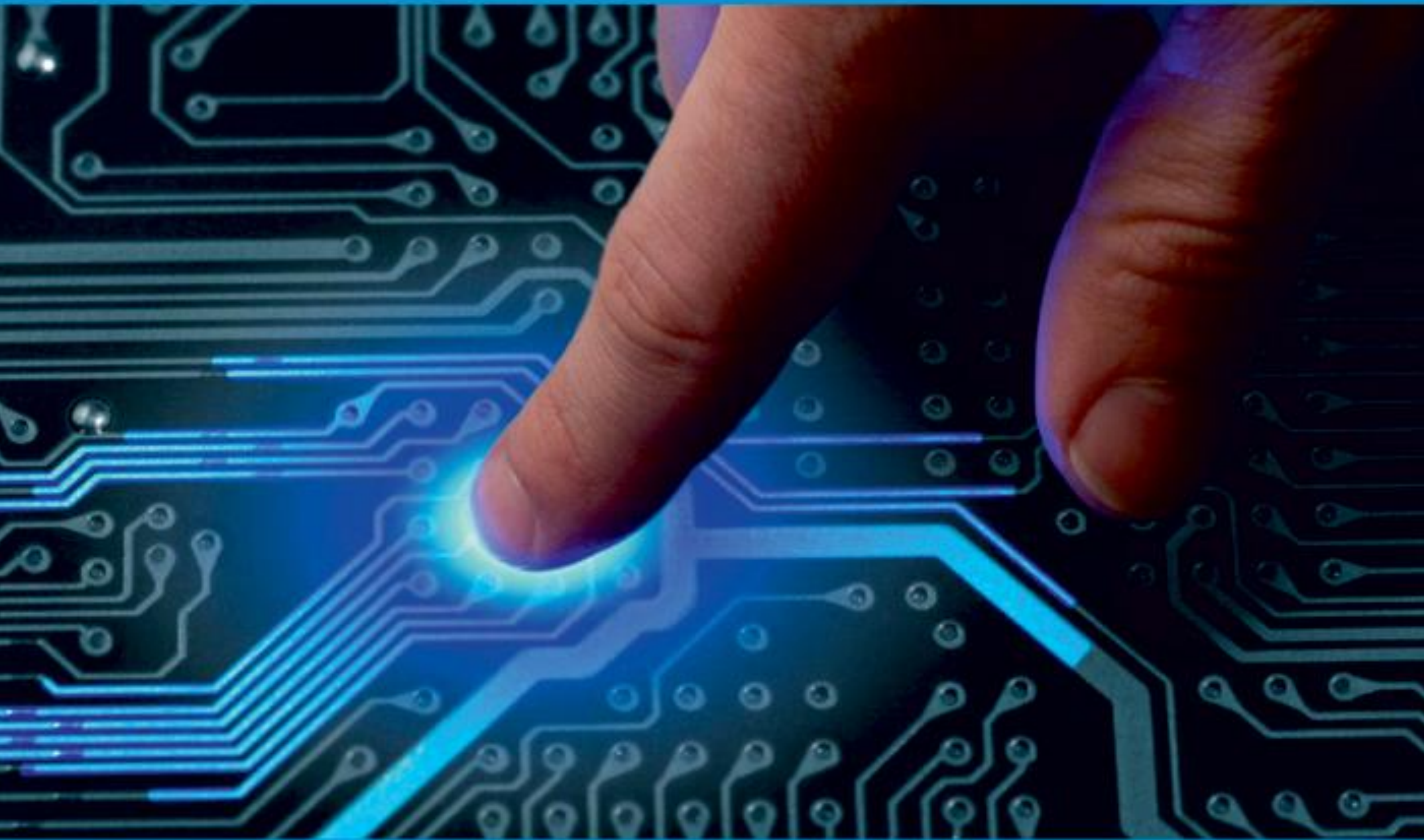

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Diabetic Retinopathy Prediction Using Machine Learning

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ABSTRACT: Diabetic Retinopathy (DR) is a retinal disease that can cause damage to blood vessels in the eye, that is the major cause of impaired vision or blindness, if not treated early. Manual detection of diabetic retinopathy is time-consuming and prone to human error due to the complex structure of the eye. Methods & Results: various automatic techniques have been proposed to detect diabetic retinopathy from fundus images. However, these techniques are limited in their ability to capture the complex features underlying diabetic retinopathy, particularly in the early stages. In this study, we propose a novel approach to detect diabetic retinopathy using a convolutional neural network (CNN) model. The proposed model extracts features using two different deep learning (DL) models, Resnet50 and Inceptionv3, and concatenates them before feeding them into the CNN for classification. The proposed model is evaluated on a publicly available dataset of fundus images. The experimental results demonstrate that the proposed CNN model achieves higher accuracy, sensitivity, specificity, precision, and f1 score compared to state-of-the-art methods, with respective scores of 96.85%, 99.28%, 98.92%, 96.46%, and 98.65%.

INDEX TERMS: Clinical and Translational Impact Statement— Diabetic Retinopathy is becoming a more common cause of visual impairment in working-age individuals. Optimal results for preventing diabetic vision loss require patients to undergo extensive systemic care. Early detection and treatment are the key to preventing diabetic vision loss, which results from long-term diabetes and causes blood vessel fluid leakage of the retina. Common indicators of DR include blood vessels, exudate, hemorrhages, microaneurysms, and texture. To address this issue, this study proposes a novel CNN model for diabetic retinopathy detection. The proposed approach is an end-to-end mechanism that utilizes Inceptionv3 and Resnet50 for feature extraction of diabetic fundus images. The features extracted from both models are concatenated and input into the pro- posed InceptionV3 Resnet50 convolutional neural network (IR-CNN) model for retinopathy classification. To improve the performance of the proposed model, several experiments, including image enhancement and data augmentation methods, are conducted. The use of DL models, such as Resnet50 and Inceptionv3, for feature extraction enables the model to capture the complex features underlying diabetic retinopathy, leading to more accurate and reliable classification results. The proposed approach outperformed the existing models for DR detection.

I. INTRODUCTION

Diabetic retinopathy is a retinal vascular disorder appears in the diabetic patients. The count of DR patients is expected to be doubled among Americans from 7.7 millionto 14.6 million between 2010 and 2050. The Hispanic Americans are expected to be affected severely and rapidly from 1.2 million to 5.3 million. The duration of diabetes is a key factor in the arrival of retinopathy, with the increase in diabetes duration will increase the risk of the DR devel- opment. It is also noticed that patients with diabetes usually unaware of the possibility of DR, which leads towards the delayed diagnosis and treatment [1]. Manual detection of DRis time-consuming and requires trained clinical experts to analyze digital color fundus images. However, the delayed outcomes can result in a lack of follow-up and misinformation for patients [2].

To develop a novel DL model for early classification ofDR using color fundus images.
To focus on the most critical aspects of the disease to exclude the irrelevant factors to ensure the high recogni-tion accuracy.

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II. RELATED WORK

In recent years, there has been a significant growth in the field of computer-aided diagnosis (CAD) in the medical industry. This emerging technology utilizes computer algo- rithms to assist medical professionals in the diagnosis of medical images. The CAD architecture is designed to address classification difficulties and has become increasingly neces- sary in the medical field [6]. Detection of DR is one of the primary goals of CAD by differentiating between infected and normal images, and analyzing various parameters such as microaneurysms (MAs), veins, texture, hemorrhages, node points, and exudate areas [4]. Machine learning (ML) basedclassification techniques are commonly used to classify the presence or absence of DR [5]. DR is normally categorized into two stages based on the number and severity of symp- toms present [7].

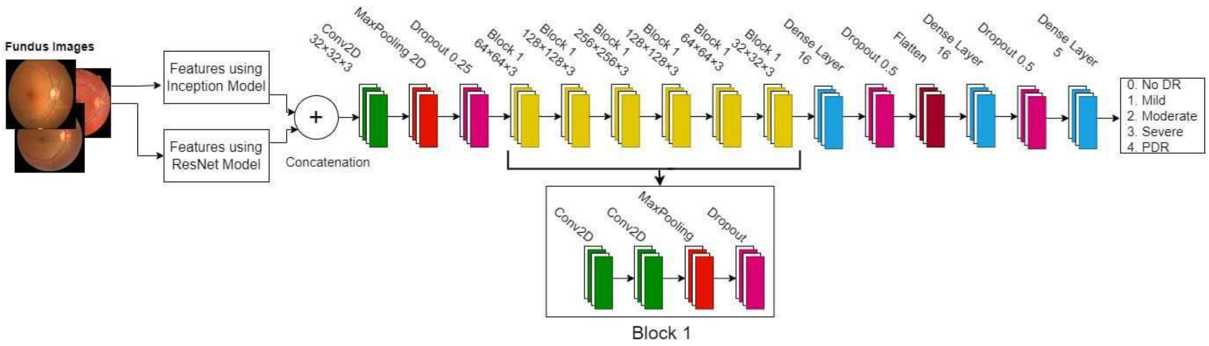

FIGURE 1. The proposed IR-CNN model for diabetic retinopathy detection.

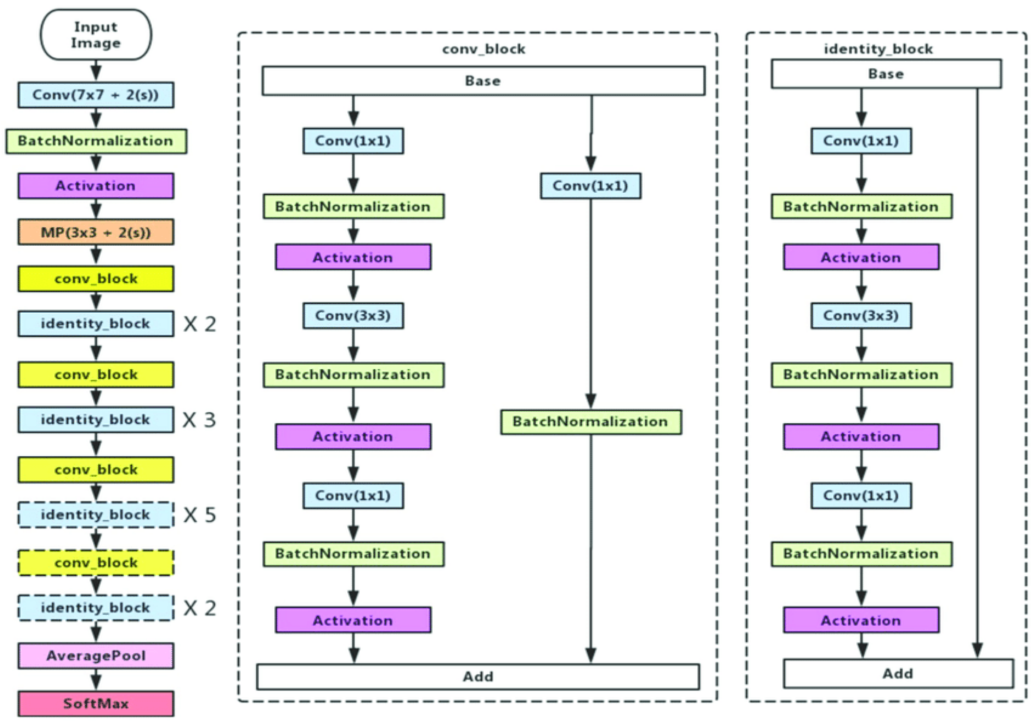

FIGURE 2. ResNet50 model used in this study.

histograms and InceptionV4 function extraction processes.The Bayesian optimization technique is used to change hyper-parameters at the initial stage of Inceptionv4. Finally, the multi-layer perceptron is used for classification processes.Test results show that the presented model provides excellentoutcomes with 99.49%, 98.83%, 99.68%, and 100% accu-racy. However, it is worth noting that this model can onlyclassify two basic DR classes, namely normal and NPDR.Furthermore, almost 70% of the investigations classified fun-dus images using binary classifiers such as DR

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or non-DR, whereas only 27% classified the input to one or more classes. In the field of DR, the use of CNN models has been explored to achieve more automated detection. In [16],
This study proposed a novel approach for the detection of DR through the use of CNNs on fundus images. Specifically, the proposed method involved conducting experiments with two distinct CNN architectures, namely Inceptionv3 and Resnet50, followed by feature extraction using these net- works. The resulting features were concatenated and used as input to the proposed CNN model for classification. To fur- ther enhance the quality of the fundus images, pre-processing techniques such as Histogram Equalization and Intensity nor- malization were applied. The experimental results demon- strate that the proposed approach outperformed existing methods for DR detection.

A.ResNet50 MODEL FOR FEATURE EXTRACTION
The ResNet50 [30] model was utilized for feature extraction from the DR images. The ResNet50 model introduced a novel structure named residual block, which is a feedforward model with a connection that allows for the addition of new inputs and the production of new outputs. This approach increases the performance of the model without significantly increasing its complexity. Resnet50 yielded the highest accuracy among the DL models considered, and thus, it was selected for DR detection.

B. Inceptionv3 MODEL FOR FEATURE EXTRACTION
In the domain of medical imaging, the InceptionV3 model, which is the most prevalent adaptation of the GoogleLeNet architecture [31]. It is extensively used for classification pur- poses. The architecture of Inceptionv3 model is illustrated in Figure 3. The InceptionV3 model is famous for fusing filters of distinct sizes to form a novel filter, resulting in a reduction of trainable parameters and a corresponding decline in computational cost.

C. EVALUATION METRICS
The objective of evaluation metrics is to assess the efficacy of ML models. Following is the brief description of performance evaluation metrics used in this research.

D. ACCURACY
The overall effectiveness of proposed model in classifying the various DR classes is evaluated using the accuracy metrics. The proportion of correctly classified and miss classified samples, divided by cumulative sum of samples, estimates the correctness of the IR-CNN model. Mathematically it is presented as:

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

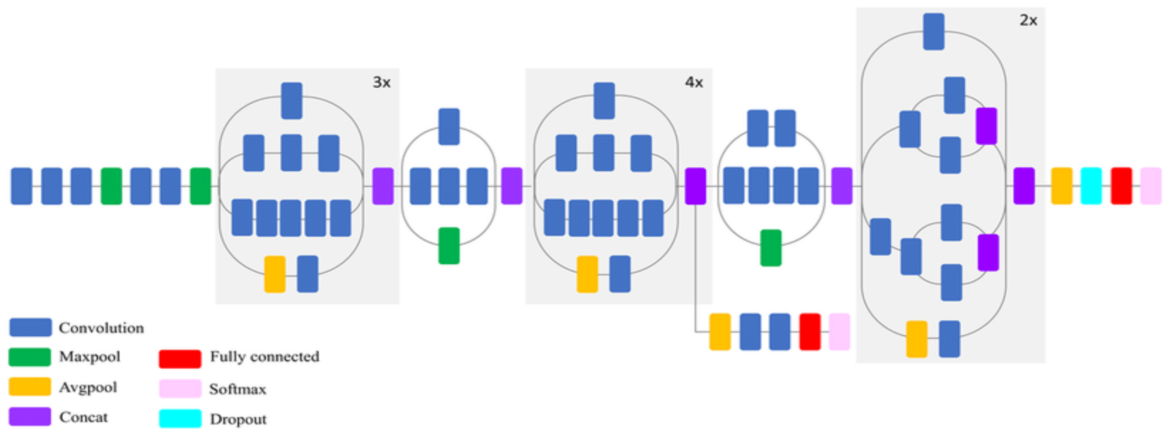

FIGURE 3. The Inceptionv3 model used in this study for diabetic retinopathy detection.

PRECISION
Precision is used to assess the ability of a ML model to precisely predict positive cases. It represents the relationshipof true positive estimates to the sum of true positive false positive estimates. Mathematically, precision can be expressed as follows:

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$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

SPECIFICITY

Specificity refers to accurately classifying the true negative cases, which is computed as the fraction of true negatives to the sum of false positive and true negatives samples. It is alsoreferred to as selectivity or true negative rate. Mathematically, specificity can be expressed as

In the world of medicine, specificity denotes to a model's ability to accurately classify samples with negative DR.

FIGURE 4. Fundus images dataset of diabetic retinopathy.

III. EXPERIMENTS AND RESULTS A. DATASET DEFINITION

In ML based medical diagnostic techniques, the quality of data is crucial for establishing the validity and generalization capabilities of models. The ML paradigm centers on con structing models that can learn from data. To this end, numerous publicly available datasets are accessible for the detection of DR and retinal vessels. These datasets serve as standard resources for training, validating, and testing ML systems, as well as for comparing the performance of different systems. Retinal imaging modalities include fundus color images and optical coherence tomography(OCT).Fundus images are two-dimensional images acquired by reflecting light, while OCT images are three-dimensional images obtained with low-coherence light that can provide structural and thickness information about the retina [32]. OCT retinal scans have been obtainable for a few years and are widely used for various purposes. In addition, a vast array of publicly available fundus images accessible for research and development in the field of ML. Individuals diagnosed with severe NPDR face a 17% probability of developing high-risk PDR within a year, and a 40%chance within three years, marking the disease's most advanced stage. PDR is characterized by the emergence of new, fragile, and anomalous blood vessels on the retina or optic nerve. The rupture of these blood vessels can lead to impaired vision. The presence of pre-retinal or vitreous hemorrhages, as well as noticeable neovascularization, is com monly detected during clinical examinations. This research utilizes an open-source dataset that is pub licly available [33]. The dataset comprises high-resolution retinal images of both left and right eyes for each patient, amounting to a total of 44,119 images. The dataset encompasses five distinct classes of DR.

A. Results before Data Augmentation

This section provides a detailed analysis and discussion of the performance of the proposed models. To quantify and assess the enhancements made to the final model, several experiments were conducted. The OCT fundus images dataset was used, and the results were obtained after selecting the best model configuration. The pre-processing step, which is an essential initial stage in every data-driven study, involved resizing the images to 256 × 256 pixels because of different image sizes of the dataset to feed into DL models.

1) Proposed IR-CNN Model

The proposed model is a hybrid model which uses features extracted from the above models described. The features from the Inceptionv3 and ResNet50 are concatenated and model without augmentation, the findings of the augmentation model were promising.

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Model	Accuracy	Sensivity	Specificity	Precision	F1 Score
IR-CNN	92.66	96.15	97.13	97.63	94.67

Table 1:. Results of the proposed IR-CNN architecture on OCT fundus images dataset

The result of all the five classes using IR-CNN is discussed in the Table 7.2, which shows the highest accuracy is achieved in class 0.

Model	Class	Label	Accuracy
IR-CNN	No DR	0	94.07
	Mild	1	92.90
	Moderate	2	92.36
	Severe	3	92.10
	PDR	4	91.90

Table 2. Result of IR-CNN model on all the classes of A

The results presented in Table 7.2 demonstrates that the proposed model IR-CNN outperform the individual model Resnet50 and InceptionV3. The proposed model achieved the classification accuracy on all classes No-DR, Mild, Moderate, Severe and PDR as 94.07%, 92.90%, 92.36%, 92.10% and 91.90% respectively, which shows the highest accuracy is achieved in class 0.

2) ResNet50 Model

After that ResNet-50 is used in this study, which has already been trained on the regular ImageNet database [34]. Residual Network-50 is a deep convolutional neural network that achieves remarkable results in ImageNet database categorization [35]. ResNet-50 is made from a variety of convolutional filter sizes to reduce training time and address the degradation problem caused by deep structures. Table 7.3 illustrate the outcomes of this model. It is found that the Resnet50 achieves accuracy, sensitivity. Specificity precision and F1 score was 84.15%, 92.58%, 89.29%, 90.47% and 93.47% respectively.

3) Inceptionv3 Model

The Inceptionv3 model is trained on the fundus images. The results of the model are presented in Table 7.5. The Inception-v3 architecture is intended for image classification and recognition. Inceptionv3 provides accuracy, sensitivity, specificity precision and F1 score as 82.97%, 94.71%, 96.12%, 94.26% and 93.79% respectively.
The result of all the five classes using InceptionV3 is discussed in the Table 5, which shows the highest accuracy is achieved in class 0.

Model	Class	Label	Accuracy
Inception v3	No DR	0	85.31
	Mild	1	82.43
	Moderate	2	8.80
	Severe	3	82.90
	PDR	4	82.04

Table 3: Result of InceptionV3 model on all the classes of DR

The results presented in Table 6 demonstrates that inceptionV3 model classifies all classes No-DR, Mild, Moderate, Severe and PDR as 85.31%, 82.43, 81.80, 82.90 and 82.04 respectively which shows the highest accuracy is achieved in class 0.

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B. Results with data Augmentation

To improve the model accuracy data augmentation methods such as scaling and rotation, are applied to all three models, which gradually increases the accuracy for all the three models. Table 7 demonstrates the results of all models with augmentation. From the results obtained one can observe the proposed model gives the highest accuracy with accuracy, sensitivity, specificity, precision and F1 score as 96.85%, 99.28%, 98.92%, 96.46% and 98.65% respectively.

Model	Accuracy	Sensivity	Specificity	Precision	F1 Score
Inception v3	87.18	95.43	93.71	94.12	90.39
RetNet50	90.65	97.75	96.48	97.25	94.28
Proposed IR-CNN Model	96.85	99.28	98.92	96.46	98.65

Table 4: Results of the InceptionV3, ResNet50, and the proposed IR-CNN model architecture on the OCT fundus images dataset

Based on the obtained results, it is evident that data augmentation has conferred benefits across all the evaluation VOLUME 11, 2023 347 G. Ali et al.: Hybrid CNN Model for Automatic DR Classification From Fundus Images criteria and has substantially enhanced the=

D. Comparison of the Proposed Method With Other DL Model

In recent years, there have been significant improvements in image classification accuracy due to advancements in DL technologies and high-performance computers. Currently, efforts are being made to create AI based techniques capable of performing ocular tasks. The Inceptionv3 model has been evaluated on OCT dataset, obtained accuracy, sensitivity, specificity, precision, and f1 score values of 87.18%, 95.43%, 93.71%, 94.12%, and 90.39%, respectively. ResNet, is a classic neural network that serves as a backbone for many computers vision tasks. the ResNet50 model yielded accuracy, sensitivity, specificity, precision, and f1 score values of 90.65%, 97.75%, 96.48%, 97.25%, and 94.28%, respectively. By combining the features of Inceptionv3 and ResNet50, the proposed model learns deep features and achieves accuracy, sensitivity, specificity, precision, and f1 score values of 96.85%, 99.28%, 98.92%, 96.46%, and 98.65%, respectively.

Method	Accuracy	Sensitivity	Specificity	Precision	F1 Score
SVM and NN	0.88	71.9	81.5	-	-
CNN	95	-	-	-	-
WP-CNN	94.23	95	90	-	0.90
SVM	91.2	90.5	91.6	-	-
REMURS-3D	80.7	-	-	-	-
Ensemble microaneurysm detector	0.87	51	96	-	-
KNN	0.87	66	93	--	--
InceptionV3,ResNEt50 And CNN Model	96.85	99.28	98.92	96.46	98.65

Table 5 Comparison of the proposed models with other DL models

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