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CNN Ensemble Learning Method for Transfer Learning: A Review

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Abstract

This study provides a review of CNN's ensemble learning method for transfer learning by highlighting sections such as review studies, datasets, pre-trained models, transfer learning, ensemble learning, and performance. The results indicate that the trend of ensemble learning, transfer learning ensemble, and transfer learning is growing every year. In 2022, there will be 35 papers reviewed related to this topic in this study. Some datasets contain apparent information starting from the dataset name, total data points, dataset splitting, target dataset availability, and type classification. ResNet-50, VGG-16, InceptionV3, and VGG-19 are used in most papers as pre-trained models and transfer learning processes. 50 (90.1%) papers use ensemble learning, and 5 (9.1%) do without ensemble learning. The reviewed paper summarizes several performance measurements, including accuracy, precision, recall, f1-score, sensitivity, specificity, training accuracy, validation accuracy, test accuracy, training losses, validation losses, test losses, training time, and AUC, DSC. In the last section, 49 papers produce the best model performance using the proposed model, and 6 other papers use DenseNet, DeQueezeNet, Extended Yager Model, InceptionV3, and ResNet-152.

Keywords: Ensemble Learning; Transfer Learning; Deep Learning; Pre-Trained Model; CNN

Introduction

Deep learning is the most common method used by researchers to detect, identify or classify [1] in many research fields, such as computer vision[2], machine translation[3], face recognition[4], or pose detection[5]. Deep learning methods are widely used because of their better performance than traditional methods or machine learning[6]–[9]. One of the most well-known is the Convolutional Neural Network (CNN), a branch of deep learning[10]. CNN has special network layer characteristics or architectures such as a convolutional layer, pooling layer, and fully connected layer[11], while other terms that are often encountered in CNN sections are input layer, feature learning, classification, and output prediction.

CNN has a collection of architectural layers such as the convolutional layer, pooling layer, and fully connected layer often referred to as the CNN model[12]. Many studies use intelligent CNN models or pre-trained models such as AlexNet, ResNet50, GoogleNet, VGG16, ResNet101, VGG19, InceptionV3, InceptionResNetV2, DenseNet, CGG19, and MobileNet[13]–[18]. One of the cases in the research conducted by [19] used a pre-trained VGG16 model with 13 layers of architecture, including feature learning which has 13 convolutional layers, and the classification section has 3 hidden layers. Pre-trained models are also often used for transfer learning [20]. Transfer learning is a process in which models that have been educated by others (pre-trained models) will be applied to problems related to their respective research cases.

The transfer learning process still needs computation time and dataset adjustment. So it is still often approached through ensemble learning to combine several transfer learning models to produce the best performance assumptions [21]. The approach through ensemble learning will build the best model.

Based on some of the explanations above, this article will discuss and review several published articles in the field of CNN ensemble learning for transfer learning which is arranged as follows: Section 2 discusses the method of selecting articles, and Section 3 discusses a review of studies. Section 4 discusses the datasets used in several publications, explaining the conceptualization of CNN in Section 5. Section 6 describes a set of pre-trained models used in several publications that have been reviewed. Section 7 discusses transfer learning, and Section 8 discusses ensemble learning from the transfer learning process, and Section 9 and 10 show the results, discussion, and conclusions accompanied by tables and figures.

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Method and Selection of Articles

This research is reviewed through articles published from 2018 to 2022 with one main reason: first, this study aims to discuss the CNN ensemble learning method for transfer learning accompanied by evaluation and performance. The evaluation of this research is based on a literature review with the selection technique illustrated in **Figure 1**. Firstly, it defines the keywords based on the research topics of review articles, such as ensemble learning, ensemble transfer learning, and transfer learning. Second, these keywords search for relevant articles using several publication databases or publishers such as IEEE, Sage Journal, Science Direct, Elsevier, Springerlink, and Scopus. Third, each relevant article is checked for each article result successfully downloaded through several publishers. This check is carried out through Mendeley, including title, abstract, tags, and information attributes. Then produced 55 articles related to this research, including CNN ensemble learning for transfer learning. Eventually, articles that meet the criteria are described as follows:

- Written in English
- Directly related to the topic of ensemble learning, ensemble transfer learning, and transfer learning
- Has provided a clear description of the methodology, datasets, algorithms, and evaluation of the model
- Published by several journals related to computer science (such as Soft Computing, Neural Computing and Application and Computer Communication) or conferences (such as IEEE Asia-Pacific Conference on Computer Science and Data Engineering and IEEE 14th International Conference on Computer Research and Development)

As a result, a total of 55 articles related to this research published from 2018 to 2022 have been selected and reviewed through method and article selection. **Figure 2**. illustrates a word cloud based on the keywords from the selected articles.

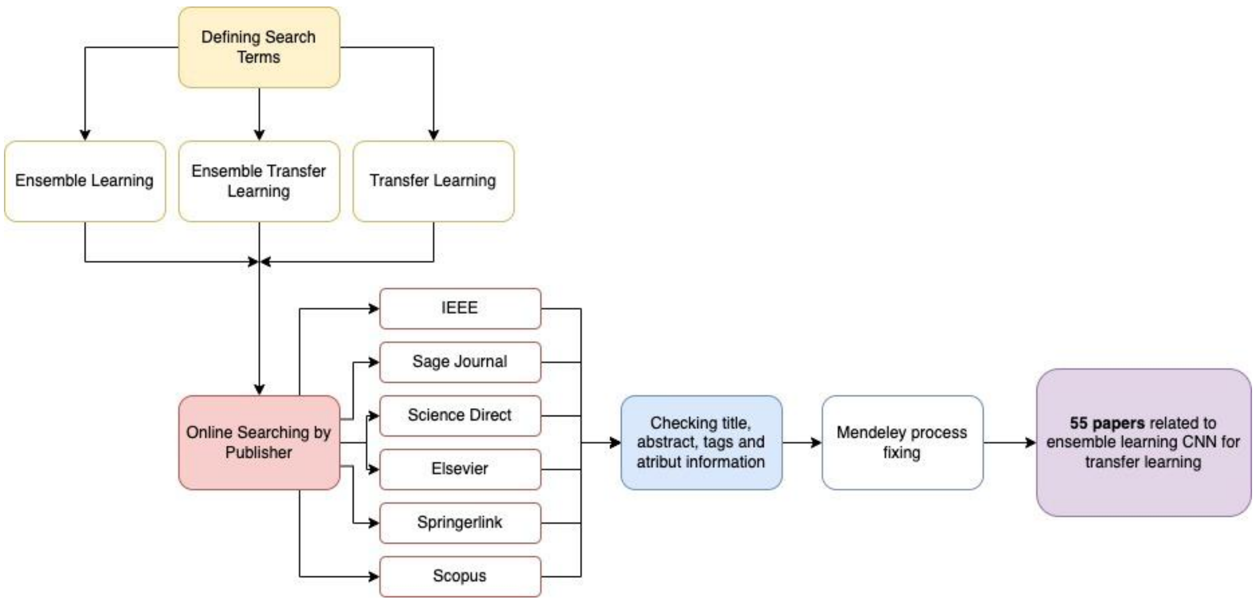

Figure 1. The method and process for selecting articles

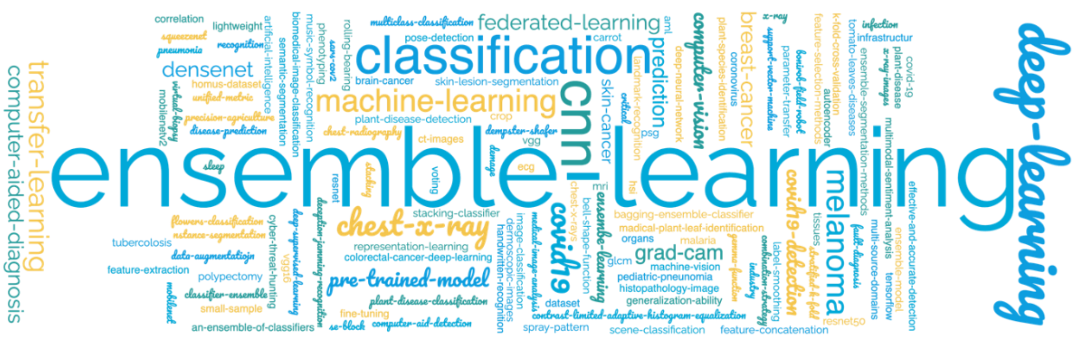

Figure 2. Word cloud based on keywords or tags in a paper review

Study Review

This study reviews the context and data to provide a more comprehensive overview of frequency and distribution. **Figure 5** illustrates the number of papers reviewed each year showing an increasing trend in general every year.

A. Knowledge Maps

This study also maps the papers that have been reviewed using tags or keywords for each paper and enables the knowledge maps to be visualized. **Figure 3** illustrates a knowledge map of interconnected networks and nodes used as part of the discussion of the paper being reviewed. **Figure 4** also illustrates a network and connected nodes on the main topic of discussion, ensemble learning. The knowledge maps that are built then produce a discussion conclusion and background in the form of several topics, such as ensemble learning, CNN, and transfer learning.

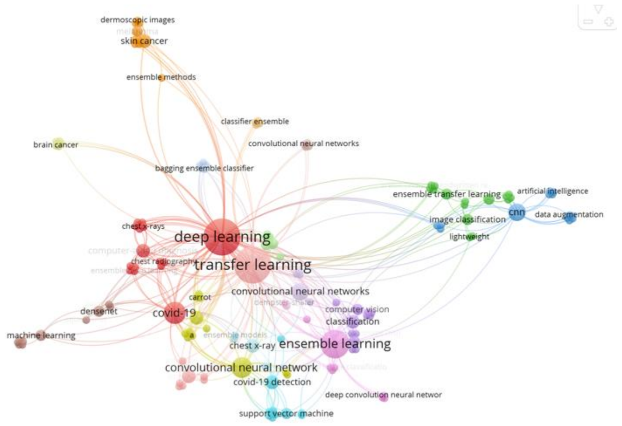

Figure 3. All knowledge maps based on the papers reviewed

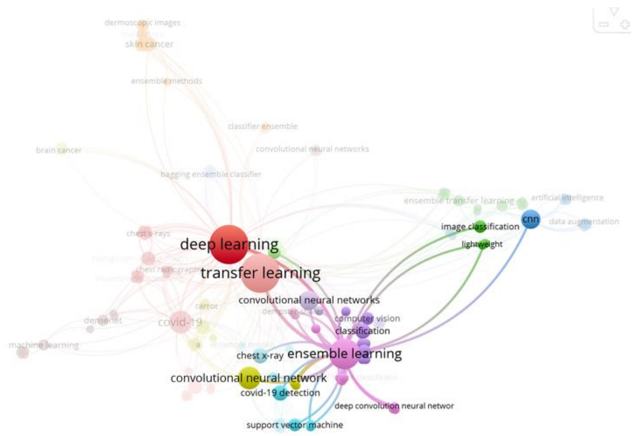

Figure 4. Knowledge maps related to CNN ensemble learning research for transfer learning

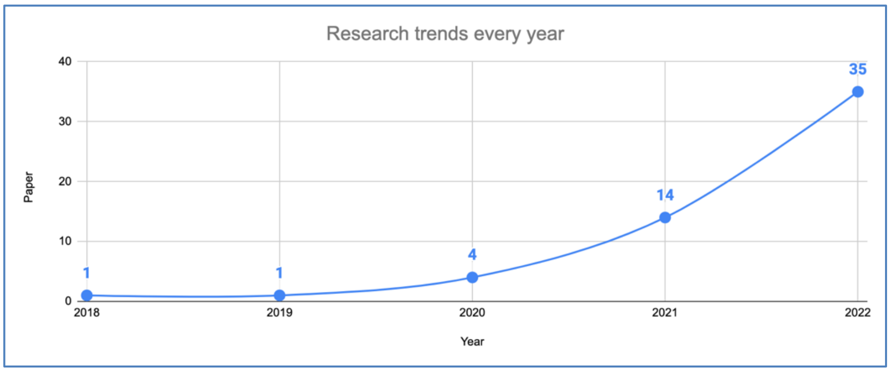

Figure 5. Number of paper reviews by year

Dataset

This study has conducted several reviews of 55 articles. Several public-minded datasets are conducted in the study [22]–[31]. Each of these public datasets is available in several paper reviews, and some are in dataset databases such as Kaggle, UCI machine learning to Google dataset search. On the other hand, in this paper review, some datasets are private or, in other words, only used in related research, as was done in research [32]–[42]. **Table 1** shows the summary of the datasets in each paper review which contains the dataset name, total data points, dataset splitting, target dataset availability, and type classification.

Table 1. Summary of the dataset in each paper review

Research	**Dataset Name**	**Total Data Point**	**Dataset Spliting**			**Target Dataset Availability**	**Type Classification**
			Train	***Validation***	***Testing***		
[32]	ECG Image	-	-	-	-	Private	-
[33]	Carrot Image	2.445	-	-	-	Private	Binary

Research	Dataset Name	Total Data Point	Dataset Spliting			Target Dataset Availability	Type Classification
			Train	*Validation*	*Testing*		
[22]	PlantVillage	54.303	-	-	-	Public	Multiclass
[23]	Pnuemonia Image	5.856	3.100	2.356	-	Public	Binary
[34]	Nozzle Image	2.333	1.401	466	466	Private	Binary
[24]	UCM	2.100	1.680	-	420	Public	Multiclass
	SIRI-WHU	2.400	1.920	-	480	Public	Multiclass
[25]	MVSA	2.892	2.024	-	868	Public	Multiclass
	T4SA	1.713.541	1.199.479	-	514.062	Public	Multiclass
[26]	SARS-COV-2 CT-Scan Dataset	2.482	1.736	-	745	Public	Binary
[27]	BreakHis	7.909	-	-	-	Public	Binary
[28]	Montgomery	138	-	-	-	Public	Binary
	Shenzhen	662	-	-	-	Public	Binary
[35]	Bearing Dataset	-	-	-	-	Private	Multiclass
[36]	ADBase & MADBase	70.000	60.000	-	10.000	Private	Multiclass
[29]	CBIS-DDSM	3.549	2.484	-	1.065	Public	Binary
[30]	Pneumonia X-Ray Dataset	6.480	5.232	624	624	Public	Multiclass
[31]	MRI Image	3.000	2.100	900	-	Public	Multiclass
[43]	X-Ray Image Dataset	11.954	7.175	1.792	2.989	Public	Multiclass
[44]	COVID-19 Chest X-Ray Dataset	2.905	2.324	465	581	Public	Multiclass
[45]	ISIC	3.297	1.977	660	660	Public	Binary
[37]	CXR or CT images	-	-	-	-	Private	Binary
[46]	TPIC2017	680.000	-	-	-	Public	Multiclass
[47]	Plant Village Dataset	43.456	34.764	-	8.692	Public	Multiclass
[48]	X-Ray Image Dataset	1.203	-	-	-	Public	Multiclass
[49]	Covid Chestxray Dataset	746	556	-	190	Public	Multiclass
[50]	LHNCBC	27.558	19.291	2.756	5.512	Public	Multiclass
[51]	ISIC 2020	33.126	29.813	2.981	3.313	Public	Binary
[52]	SDH2019.2	21.700	19.530	-	2.170	Public	Multiclass
[53]	BRATS	423	-	-	-	Public	Binary
[54]	COVID-19 Datasets	9.300	7.905	-	1.395	Public	Multiclass
[55]	CT Images	8.347	5.342	1.336	1.669	Public	Multiclass
[56]	COVID-19 Radiography Database	2.905	2.324	-	581	Public	Multiclass
	IEEE COVID Chest X-Ray Dataset	846	677	-	169	Public	Binary
[57]	Chest X-ray Images	6.087	4.870	-	1.217	Public	Binary
[58]	LANDSAT	7.000	4.900	-	2.100	Public	Binary
[38]	Cardiovascular Dataset	13.500	4.200	1.800	7.500	Private	Multiclass
[39]	Chest X-ray Images	401	246	82	73	Private	Binary
[59]	2D Hela Dataset	1.000	800	-	200	Public	Multiclass
	PAP Smear Dataset	917	734	-	183	Public	Multiclass
	Hep-2 Cell Image Dataset	1.455	721	-	734	Public	Multiclass
[60]	COVID-CT Dataset	746	425	118	203	Public	Binary
	Covid-19 Image Data Collection	579	309	70	200	Public	Binary

Research	Dataset Name	Total Data Point	Dataset Spliting			Target Dataset Availability	Type Classification
			Train	*Validation*	*Testing*		
	COVID-CTset	12.058	11.400	258	400	Public	Binary
	COVID-19 Radiography Database	2.541	3.086	400	400	Public	Binary
	SARS-CoV-2 CT scan dataset	2.482	1.800	282	400	Public	Binary
[61]	Leaf Image	1.841	1.547	-	294	Public	Multiclass
[40]	SWaT Dataset	449.920	-	-	-	Private	Multiclass
[62]	COVID-19 CT	746	448	112	186	Public	Binary
[63]	ChestX-Ray14 Dataset	112.120	86.524	25.596	7.750	Public	Multiclass
[64]	PICCOLO	3.433	2.203	897	333	Public	Multiclass
	CPDC	3.100	1.100	1.000	1.000	Public	Binary
[65]	HOMUS	15.200	10.640	2.280	2.280	Public	Multiclass
[66]	MELANOMA	246	172	-	74	Public	Binary
[67]	Tomato Leaves	18.160	13.360	-	4.800	Public	Multiclass
[68]	Plant Image	17.543	14.446	-	3.097	Public	Multiclass
[69]	UBD_45	1.232	986	123	123	Public	Multiclass
	VP_200	20.000	12.000	4.000	4.000	Public	Multiclass
[41]	Paddy Crop Image	-	-	-	-	Private	Multiclass
[70]	Plant Disease	54.306	43.445	-	10.861	Public	Multiclass
[71]	Flower Dataset	4.323	3.890	-	3.890	Public	Multiclass
[72]	Oxford-17 Flowers Dataset	1360	1.020	170	170	Public	Multiclass
	Oxford-102 Flowers Dataset	8.189	6.149	1.020	1.020	Public	Multiclass
[42]	POSE	90.000	7.200	1.800	1.800	Private	Multiclass
[73]	Indian Pines	10.250	-	-	-	Public	Multiclass
	KSC	5.211	-	-	-	Public	Multiclass
	Houston	-	-	-	-	Public	Multiclass
[74]	Road Sign	4.000	3.200	-	800	Public	Multiclass
[75]	ISIC-2017	2.750	2.000	150	600	Public	Multiclass
	PH2 DATASET	200	-	-	-	Public	Multiclass

Convolutional Neural Network (CNN)

Convolution Neural Network (CNN) is a structured and computationally integrated artificial neural network, which is one of the representative algorithms for deep learning. The efficiency of image classification based on deep learning is significantly improved compared to traditional image classification methods[76]–[78]. CNN has experienced many significant developments from its predecessor, namely MLP or multi-layer perception[79]. This development of CNN produce the architecture as shown in **Figure 6**, which generally consists of feature learning and classification [80].

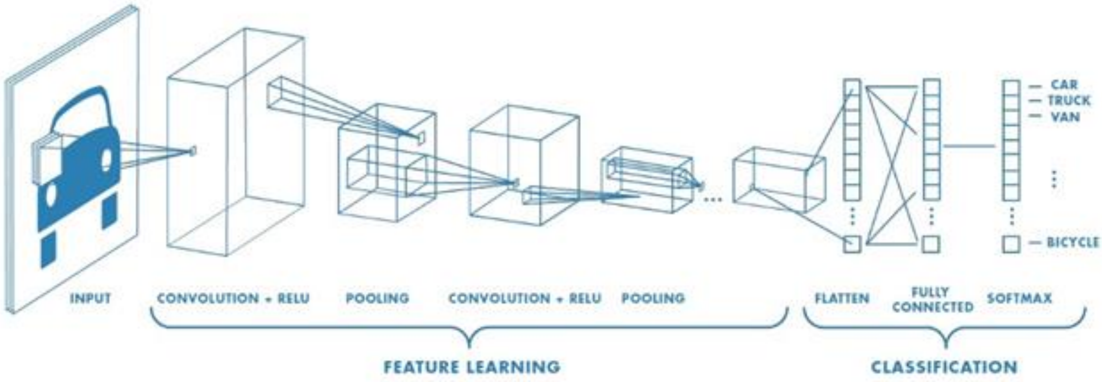

Figure 6. Feature learning and classification on the CNN Architecture

A. Feature Learning

CNN basically adopts the term feature learning to extract an image into values that represent that image[81]. Feature learning has several basic parts, such as the convolutional and pooling layers. Although, there are still many layers that can be applied to feature learning [82]. The application of several layers in feature learning can generally be discussed in these two sections, including:

- Convolutional Layer

  Input has 3 parts consisting of width x height x image dimensions. The 1st dimension image will be transformed into black, white or gray and the 3rd dimension image will be transformed into red, green and blue. An example of the convolution process using an image with a size of 9x9x1 with a kernel size of 3x3 and a stride of 2 can be seen in **Figure 7**.

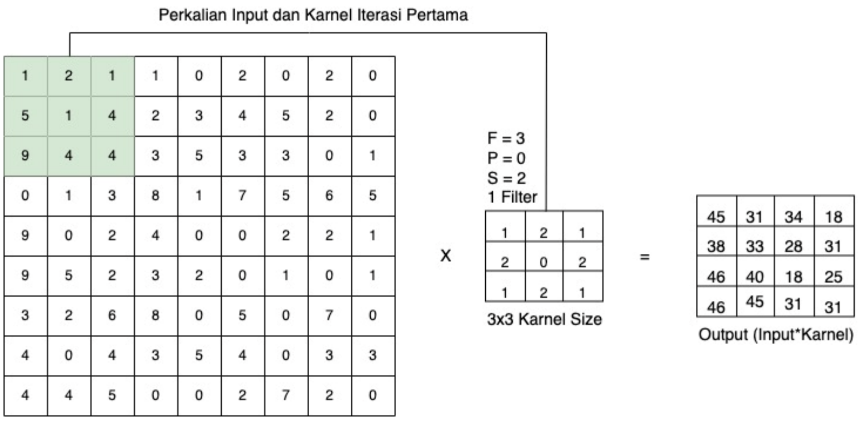

Figure 7. Simple convolutional layer process

- *Pooling Layer*

  Max Pooling aims to reduce the number of parameters by an operation known as down-sampling. One of the max pooling processes using the convolution output results in **Figure 7** with an image size of 4x4x1 with a stride of 2 can be seen in **Figure 8**.

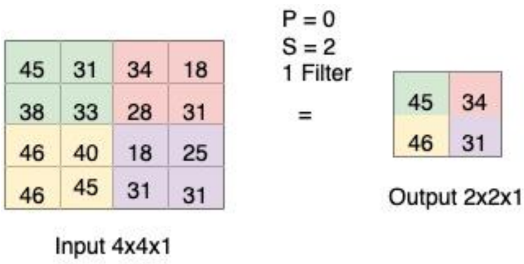

Figure 8. Max pooling simple process

B. Classification

The feature map produced from Feature Learning is still in the form of a multidimensional array, so it must "flatten" or reshape the feature map into a vector so that it can be used as input from the fully-connected layer. The last layer in feature learning with neurons in the fully connected layer can be seen in **Figure 9**.

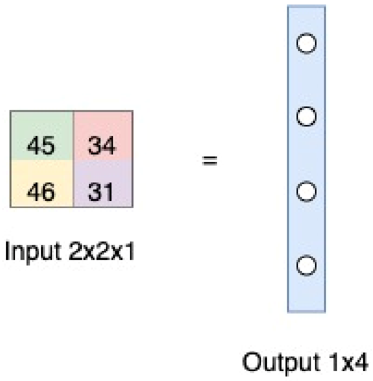

Figure 9. Simple fully connected layer (flatten) process

Pre-Trained Model

The approach through pre-trained models is used for feature learning or in-depth extraction of features prepared for custom datasets [1]. Many stable pre-trained models are used today such as: MobileNetV2, MobileNet, EfficientNetB0, DenseNet-121, DenseNet-169, DenseNet-201, VGG-16, Xception, InceptionV3, VGG-19, ResNet-50V2, ResNet- 50, ResNet-101V2, ResNet-101, ResNet-152V2, ResNet-152, InceptionResNetV2 which have been used in research [23]. This pre-trained model has an architecture that includes feature learning and classification, such as VGG-16, which has 13 layers, 10 in the feature learning section and 3 in the classification section. **Table 2** describes in detail the pre-trained model used in the reviewed paper.

Table 2. Summary of the pre-trained model and the total layers

No	Pre-Trained Model	Total Layer	No	Pre-Trained Model	Total Layer
1	AlexNet	8	20	MobileNetV2	53
2	CheXnet	121	21	MobileNetV3	26
3	DeTrac	10	22	NASNetLarge	87
4	DeepLabV3+	101	23	NASNetMobile	152
5	DenseNet-121	121	24	ResNet-101	101
6	DenseNet-161	161	25	ResNet-101V2	101
7	DenseNet-169	169	26	ResNet-152	152
8	DenseNet-201	201	27	ResNet-152V2	152
9	EfficientNetB0	237-813	28	ResNet-18	18
10	EfficientNetB1	237-814	29	ResNet-34	34
11	EfficientNetB2	237-815	30	ResNet-50	50
12	EfficientNetB3	237-816	31	ResNet-50V2	50
13	EfficientNetB4	237-817	32	SeResnet-50	50

No	Pre-Trained Model	Total Layer	No	Pre-Trained Model	Total Layer
14	EfficientNetB5	237-818	33	ShuffleNet	50
15	GoogleNet	22	34	SqueezeNet	18
16	InceptionResNetV2	467	35	VGG-11	11
17	InceptionV3	48	36	VGG-16	16
18	LeNet	7	37	VGG-19	19
19	MobileNet	28	38	Xception	71

Modifications to the pre-trained model are carried out using a custom dataset. This is done to adjust the classification section to the dataset's number of classes/labels/outcomes. Modification is often called the base model layer in several studies [43], [45], [48], [52], [83]. Conceptually the base model layer is part of feature learning and classification [84]. The main challenge in determining the base model layer that fits the background of the research case has to have different experimental approaches, as was done by [24], [25], [29], [35], [36] to produce the best model, when the transfer learning process is carried out from the pre-trained model to the base model layer. **Figure 10** illustrates the use of the pre-trained model in the paper being reviewed.

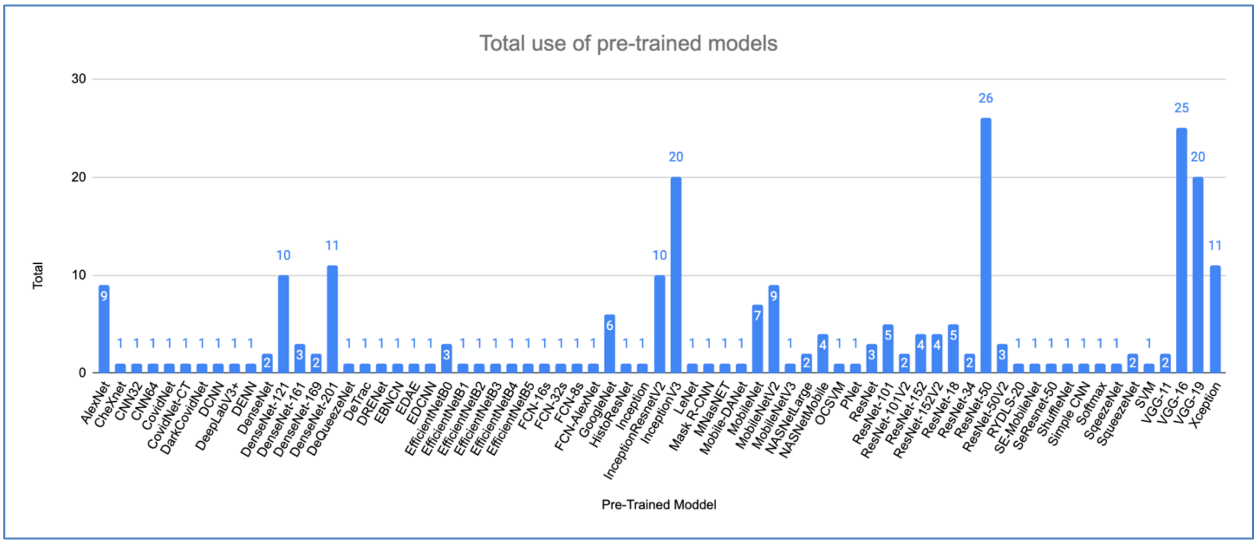

Figure 10. Total use of pre-trained models

Transfer learning

Transfer learning is carried out in the pre-trained model process for feature learning against the base model layer for a combination of feature learning and classification or only the classification part itself. This transfer learning process can achieve better models or learning outcomes [22]. In the paper that has been reviewed [14], applying CNN-TL or the well-known pre-trained model AlexNet, VGG-16, VGG-19, ResNet50, and GoogleNet for word image recognition and on the base model layer used for experiments consisting of 7 convolutional layers. In simple terms, this research will discuss the basic conceptualization of the transfer learning process in general, including:

A. Define Pre-Trained Model

VGG-16 [58] is a pre-trained model with good architecture. This pre-trained model has a feature learning and classification section and has 16 layers, according to **Table 2**. However, in this study, only 13 layers were used, specifically in the feature learning section with architecture, which can be seen in **Figure 11**.

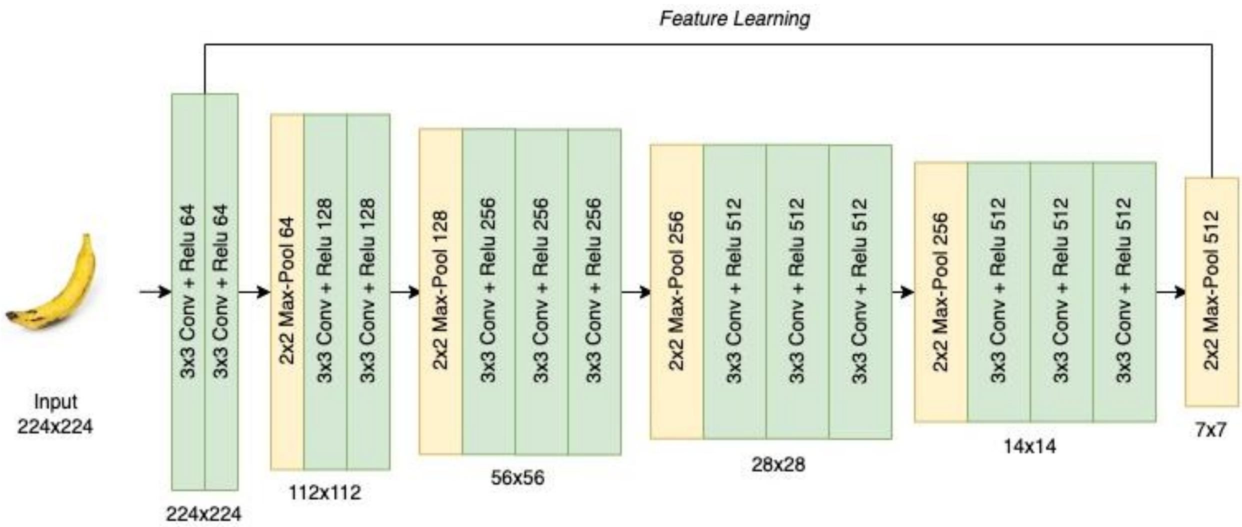

Figure 11. Layer architecture of the pre-trained model VGG16

B. Base Model Layer

In this paper review, the process of defining the base model layer or the architectural design of the CNN layer is carried out based on assumptions and independent experiments. The design of the CNN layer architecture includes its feature learning and classification sections with several layers, including 4 convolutional layers, 3 pooling layers, and a fully connected layer, as shown in **Figure 12**.

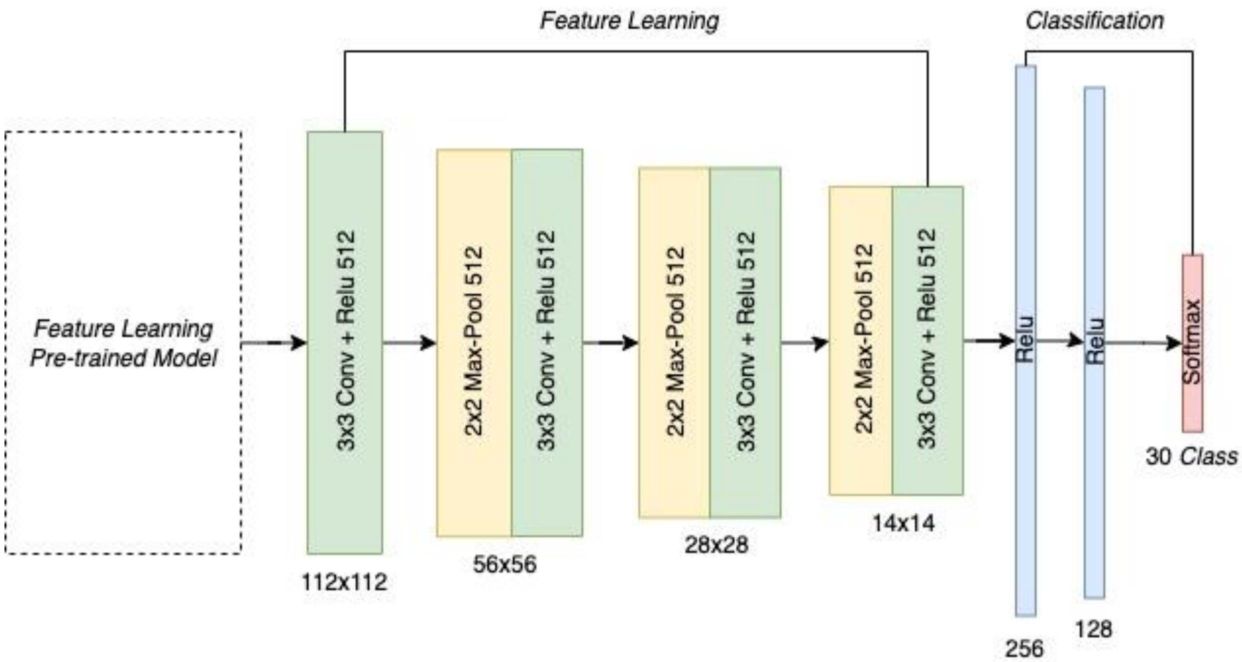

Figure 12. CNN base model layer design

C. Process

The process of combining layer architecture in the pre-trained model (VGG16) with architectural designs based on assumptions and independent experiments is called transfer learning. Initially, the pre-trained model architecture consisted of 16 layers, then in the VGG16 classification section, it was removed to 13 layers. The base model layer uses 4 additional layers in feature learning and 3 additional layers in the classification section, which can be seen in **Table 3**.

Table 3. Layer structure after transfer learning

No	Layer	Input	Filter	Karnel Size	Strides	Activation Function
1	Convolution	224x224	64	3x3	-	Relu

No	Layer	Input	Filter	Karnel Size	Strides	Activation Function
2	Convolution	224x224	64	3x3	-	Relu
3	Max Pooling	112x112	64	-	2x2	Relu
4	Convolution	112x112	128	3x3	-	Relu
5	Convolution	112x112	128	3x3	-	Relu
6	Max Pooling	56x56	128	-	2x2	Relu
7	Convolution	56x56	256	3x3	-	Relu
8	Convolution	56x56	256	3x3	-	Relu
9	Max Pooling	28x28	256	-	2x2	Relu
10	Convolution	28x28	512	3x3	-	Relu
11	Convolution	28x28	512	3x3	-	Relu
12	Convolution	28x28	512	3x3	-	Relu
13	Max Pooling	14x14	256	-	2x2	Relu
14	Convolution	14x14	512	3x3	-	Relu
15	Convolution	14x14	512	3x3	-	Relu
16	Convolution	14x14	512	3x3	-	Relu
17	Max Pooling	7x7	512	-	2x2	Relu
18	Convolution	112x112	512	3x3	-	Relu
19	Max Pooling	56x56	512	-	2x2	Relu
20	Convolution	56x56	512	3x3	-	Relu
21	Max Pooling	28x28	512	-	2x2	Relu
22	Convolution	28x28	512	3x3	-	Relu
23	Max Pooling	14x14	512	-	2x2	Relu
24	Convolution	14x14	512	3x3	-	Relu
25	Dense	256	-	-	-	Relu
26	Dense	128	-	-	-	Relu
27	Dense (Output)	30	-	-	-	Softmax

Ensemble Learning

Ensemble learning combines two or more predictions of learning outcomes or models that can improve performance compared to single learning outcomes or single models [85] in the review paper [71] applying ensemble learning from several pre-trained models VGG-16, ResNet-50, MobileNetV2 for flower classification and showing that the ensemble learning approach outperforms each of the three previous methods. **Figure 13** shows the general concept of working ensemble learning. Ensemble learning works on several models. Then these models are fit or trained to predict learning outcomes or models. After that, an ensemble learning process is carried out to combine several of these models to become the best model or the best model. **Figure 14** shows the number and percentage of articles using and without ensemble learning.

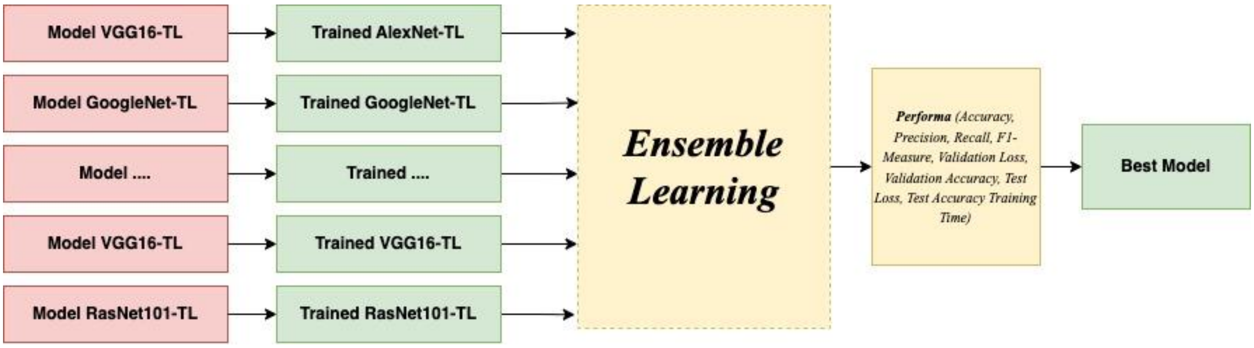

Figure 13. Ensemble learning process flow

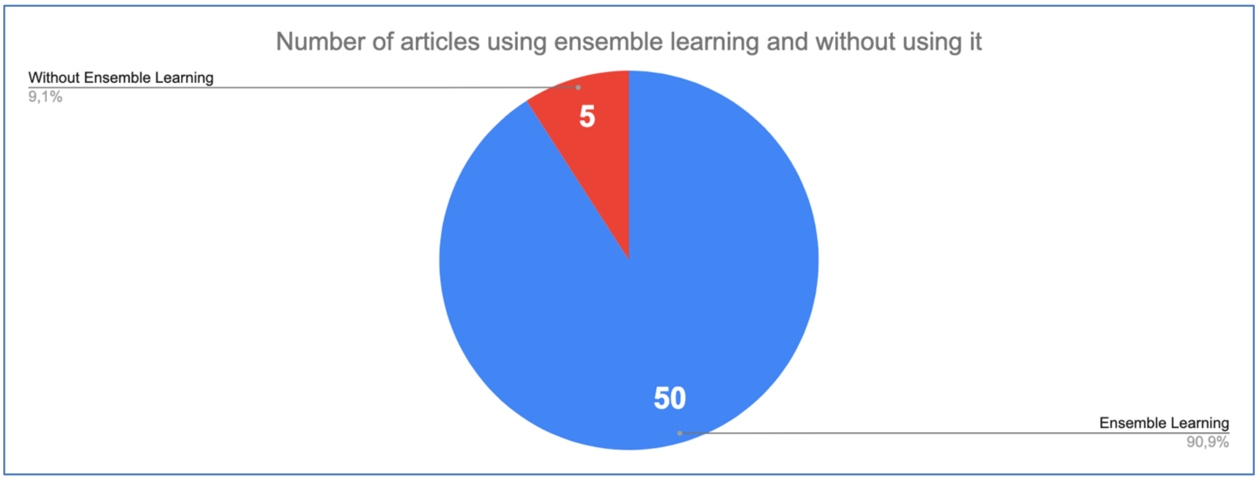

Figure 14. Presentation of papers reviewed using and without using ensemble learning

Performance

In general, the performance evaluation measurements usually use: accuracy, precision, recall, and f-measure by most articles reviewed. It is carried out after the combination process in ensemble learning, which is measured based on several general performance measurements [86]. The papers that have been reviewed in **Table 4** shows the performance results of each paper review. Performance evaluation is based on the best model after the ensemble learning process. In some of the papers reviewed, many performance evaluation techniques are summarized, starting from accuracy, precision, recall, f1-score, sensitivity, specificity, training accuracy, validation accuracy, test accuracy, training losses, validation losses, test losses, training time, AUC, DSC.

Table 4 Shows performance evaluation based on the papers reviewed.

Research	Best Model	ACC	PRE	REC	F1	SE	SP	TRA	VAA	TEA	TRL	VAL	TEL	TT	AUC	STD	DSC
[32]	WECCN-TL	-	-	0.93	0.93	-	-	0.95	-	-	0.62	-	-	187.35	-	-	-
[33]	R-D-V16	0.97	0.99	-	0.97	0.95	0.99	-	-	-	-	-	-	-	-	-	-
[22]	Es-MbNet	-	-	-	-	-	-	0.98	0.98	-	6108	5808	-	-	-	-	-
[23]	Proposed Method	0.99	1.00	0.99	0.99	-	-	-	-	-	-	-	-	-	-	-	-
[34]	Proposed Ensemble	0.99	0.99	0.97	0.98	-	-	-	-	-	-	-	-	-	-	-	-
[24]	Ensemble	0.99	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[25]	Extended Demster Shafer (Yager) Model	0.97	0.95	0.98	0.96	-	-	-	-	-	-	-	-	-	-	-	-
[26]	Proposed ET-NET	0.98	0.98	0.98	0.98	-	-	-	-	-	-	-	-	-	0.98	-	-
[27]	Proposed Method	0.97	0.97	0.97	0.97	-	-	-	-	-	-	-	-	-	0.97	-	-
[28]	Proposed Method	0.90	-	-	-	-	-	-	-	-	-	-	-	-	0.94	-	-
[35]	Proposed Method	0.99	-	-	-	-	-	-	-	-	-	-	-	216.44	-	0.2	-
[36]	EDTL Model	0.99	1.0	1.0	-	-	-	-	-	-	-	-	-	-	-	-	-
[29]	Proposed Model (Class BM-	0.95	-	-	-	0.93	0.93	-	-	-	-	-	-	-	-	-	-

Research	Best Model	ACC	PRE	REC	F1	SE	SP	TRA	VAA	TEA	TRL	VAL	TEL	TT	AUC	STD	DSC
	MM)																
[30]	Ensemble	0.96	-	-	-	0.98	0.93	-	-	-	-	-	-	-	0.95	-	-
[31]	Voting Ensemble	0.97	0.96	-	-	-	0.96	-	-	-	-	-	-	-	0.95	-	0.95
[43]	Stacking Ensemble	0.98	0.99	1.00	0.99	-	-	-	0.98	0.99	-	-	-	-	-	-	-
[44]	Proposed Method	0.95	0.95	0.96	0.95	-	0.97	-	-	-	-	-	-	-	-	-	-
[45]	Stacking Ensemble	0.96	0.96	0.97	0.96	-	0.95	-	-	-	-	-	-	-	0.95	-	-
[37]	Proposed Model	0.998	-	-	-	1.0	0.998	-	-	-	-	-	-	-	-	-	-
[46]	Proposed hybrid model	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[47]	Proposed DENN	-	1.00	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[48]	Proposed Ensemble	0.96	0.95	0.96	0.96	0.96	0.95	-	-	-	-	-	-	-	-	-	-
[49]	Proposed SA-TSA	0.97	0.99	-	0.97	0.97	0.99	-	-	-	-	-	-	-	-	-	-
[50]	Proposed Model	0.98	0.98	0.98	0.98	-	-	-	-	-	-	-	-	-	-	-	-
[51]	Proposed Model	-	0.16	0.04	0.23	-	-	-	-	-	-	-	-	-	-	-	-
[52]	Ensemble	0.99	-	0.99	0.99	-	-	-	-	-	-	-	-	-	-	-	-
[53]	Proposed Model	0.99	1.00	-	0.99	0.99	1.00	-	-	-	-	-	-	168	-	-	-
[54]	Proposed Model	0.99	0.99	0.99	0.99	-	-	-	-	-	-	-	-	-	-	-	-
[55]	Prediction Voting	0.95	0.95	0.95	0.95	-	-	-	-	-	-	-	-	-	-	-	-
[56]	Proposed Model	0.99	0.99	-	0.99	-	-	-	-	-	-	-	-	-	-	-	-
[57]	Proposde Model	0.95	0.95	-	0.95	0.94	0.98	-	-	-	-	-	-	78.86	-	-	-
[58]	Proposed Model	0.98	0.98	0.79	0.88	-	-	-	-	-	-	-	-	-	-	-	-
[38]	Proposed Model	-	0.88	0.87	0.87	-	-	-	-	-	-	-	-	-	-	-	-
[39]	DeQueeze Net	0.94	0.90	0.96	-	-	-	-	-	-	-	-	-	-	-	-	-
[59]	Proposed Model	-	-	-	-	-	-	0.95	-	-	1.13	-	-	-	-	-	-
[60]	Proposed Model	0.99	0.99	1.00	0.99	-	-	-	-	-	-	-	-	-	-	-	-
[61]	Proposed Model	0.99	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[40]	Proposed Model (Centralized)	0.97	0.99	0.99	0.99	-	-	-	-	-	-	-	-	497.8	-	-	-
[62]	Proposed Model	0.85	0.85	0.85	0.85	-	-	-	-	-	-	-	-	-	0.91	-	-

Research	Best Model	ACC	PRE	REC	F1	SE	SP	TRA	VAA	TEA	TRL	VAL	TEL	TT	AUC	STD	DSC
[63]	Proposed Model	0.99	-	-	0.98	0.98	0.99	-	-	-	-	-	-	-	-	-	-
[64]	Proposed Model (Weiighted Average)	0.81	0.82	0.80	0.81	0.80	0.81	-	-	-	-	-	-	-	-	-	-
[65]	Proposed Model (Fornes *Dataset*)	-	1.00	1.00	1.00	1.00	-	-	-	-	-	-	-	1.15 (minutes)	-	-	-
[66]	Majority Voting	0.95	-	-	0.95	-	-	-	-	-	-	-	-	-	0.98	-	-
[67]	Proposed Model	0.98	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[68]	Proposed Model	-	0.9927	-	0.9926	0.9926	-	0.9997	-	9.926	-	-	-	0.005309	-	-	-
[69]	Stacking Ensemble	98.41	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[41]	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[70]	DenseNet	0.99	0.98	0.98	0.98	-	-	1.00	0.99	-	-	-	-	-	-	-	-
[71]	Proposed CNN Framework	-	-	-	-	-	-	-	0.95	0.91	-	-	-	-	-	-	-
[72]	InceptionV3	-	-	-	-	-	-	0.99	-	-	0.01	0.29	-	-	-	-	-
[42]	ResNet-152	0.95	0.88	0.90	0.95	-	-	-	-	-	-	-	-	-	-	-	-
[73]	TCNN-E (KSC *Dataset*)	-	0.99	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[74]	Proposed Model	0.98	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[75]	Ensemble-S	0.94	-	-	-	0.93	0.92	-	-	-	-	-	-	-	-	-	-

Findings and Discussions

In total, there were 55 papers reviewed in the final review. **Table 1** summarizes the dataset, which contains information on total data points. Total data splitting includes training, validation and testing, target dataset availability, and task classification. **Table 2** shows 38 pre-trained models used in the paper reviewed. Some of the pre-trained models often used in the papers reviewed include: ResNet-50 was used 26 times. VGG-16 was used 25 times, InceptionV3 was used 20 times, and VGG19 was used 20 times. The others are shown in **Figure 10**.

This study found that 50 (90.9%) papers were reviewed using ensemble learning and 5 (9.1%) without ensemble learning, based on **Figure 14**. Papers that carry out an ensemble learning approach often use the term proposed model or approach through ensemble learning.

The approach with ensemble learning is very good for the final decision regarding the model's performance. **Table 4** illustrates the performance evaluation based on the papers reviewed. The performance evaluation is summarized based on several measurements, including accuracy, precision, recall, f1-score, sensitivity, specificity, training accuracy, validation accuracy, test accuracy, training losses, validation losses, test losses, training time, AUC, and DSC. 49 papers produce the best model performance using the proposed model, and 6 other papers consist of DenseNet, DeQueezeNet, Extended Yager Model, InceptionV3, and ResNet-152. Meanwhile, the final part relates to the CNN ensemble learning method for transfer learning, as illustrated in **Figure 15**.

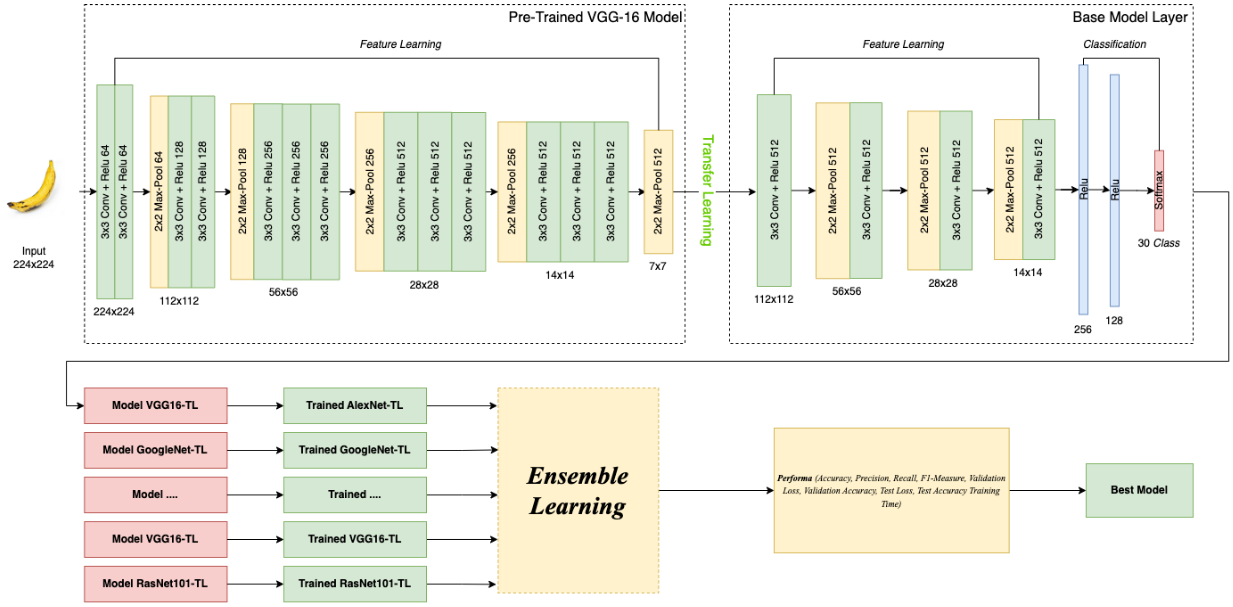

Figure 15. The flow diagram of the ensemble learning method.

Conclusion

The use of CNN ensemble learning for transfer learning is highly developed, especially in applying pre-trained models. This research provides insight into CNN ensemble learning for transfer learning based on 55 papers reviewed from 2018 to 2022. This review is classified into several sub-sections: a review of studies, datasets, pre-trained models, transfer learning, ensemble learning, and performance. Trends in the topic of ensemble learning, ensemble transfer learning, and transfer learning are developing every year. In 2022, there will be 35 papers reviewed related to this topic in this research. Some datasets contain very clear information, starting from the dataset name, total data points, dataset splitting, target dataset availability, and type classification. ResNet-50, VGG-16, InceptionV3, and VGG-19 are used in most papers as pre-trained models and transfer learning processes. 50 (90.1%) papers use ensemble learning, and 5 (9.1) do without ensemble learning. The reviewed paper summarizes several performance measurements, including accuracy, precision, recall, f1-score, sensitivity, specificity, training accuracy, validation accuracy, test accuracy, training losses, loss, and loss, training time, AUC, and DSC. The 49 papers that produced the best model performance used the proposed model, and 6 other papers used DenseNet, DeQueezeNet, Extended Yager Model, InceptionV3, and ResNet-152.

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