Optimizing Image Classification Performance with MnasNet Model on Blurred Images

[1]Rani Puspita, [2]Zahra Nabila Izdihar
[1,2]Computer Science Department, School of Computer Science, Bina Nusantara University, Indonesia
Email: [1]rani.puspita@binus.ac.id, [2]zahra.izdihar@binus.ac.id

Article Info
Article history:
Received Mar 27th, 2024
Revised May 19th, 2024
Accepted May 23th, 2024

Keyword:
Deep Learning Approach
Evaluation
Fashion Industry
Image Classification
MnasNet

ABSTRACT
In this era, the development of fashion in clothing is increasing. Over the last 30 years, the fashion industry has experienced significant improvements, causing its growth and development to increase. Fashion has many types and variants, but blurry images can also make it difficult for people to classify whether this is a shirt, t-shirt, or something else. Because of that, we proposed image classification. By classifying images, we can help the fashion industry to separate categories and types of various fashion. The approach uses MnasNet which is included in the deep learning approach. The data used is 70,000 which is divided into 60,000 training data and 10,000 testing data. The MnasNet architectural model produces an accuracy of 89% and a loss of 0.4426. It can be seen that MnasNet is the right method for image classification so that the problems described in the background have been successfully solved.

Corresponding Author:
Rani Puspita,
Computer Science Department, School of Computer Science, Bina Nusantara University,
Jakarta, Indonesia 11480.
Email: rani.puspita@binus.ac.id
DOI: http://dx.doi.org/10.24014/ijaidm.v7i2.29571

1. INTRODUCTION

In this era, the development of fashion in clothing is increasing. Over the last 30 years, the fashion industry has experienced significant improvements, causing its growth and development to increase. Developments in the world of fashion make it difficult for people to recognize the latest fashion variations because fashion has many types and variants, for example for the tops, there will be many variations such as sweaters, dresses, vests, shirts, and others [1]. Besides that, blurry images can also make it difficult for people to classify whether this is a shirt, t-shirt, or something else. This is in line with other research which states that, the fashion market is also increasingly unpredictable. Competition has changed substantially in recent decades. Currently, the fashion industry also has difficulty understanding customer tastes. By understanding this, then sales of fashion will be better and profits will increase [2].

Currently there is a Fashion-MNIST dataset which is a dataset taken from a collection of fashion product images on the Zalando website [3]. Many images have low resolution, noise, and missing data, which can hinder their interpretation and analysis. So, the results of the analysis will be far from accurate. Traditional method of image enhancement has limitations, such as the length of processing time required [4]. Blurry images can be caused by motion blur, out of focus, etc. These factors can affect the image resolution, thereby resulting loss of detail in the image. Previously there was a dataset in the form of handwritten MNIST numbers from LeCun, et al which is the dataset most used as a testing dataset for deep learning methods [5]. The reason MNIST has become so popular has to do with its size, which allows deep learning researchers to quickly prototype their algorithms [3]. The Fashion-MNIST dataset has the same number and size as MNIST but with different classification types. The Fashion-MNIST classification is T-Shirt/Top, Trouser, Pullover, Dress, Coat, Sandals, Shirt, Sneaker, Bag and Ankle boots [6]. The classification can be seen in the image below:

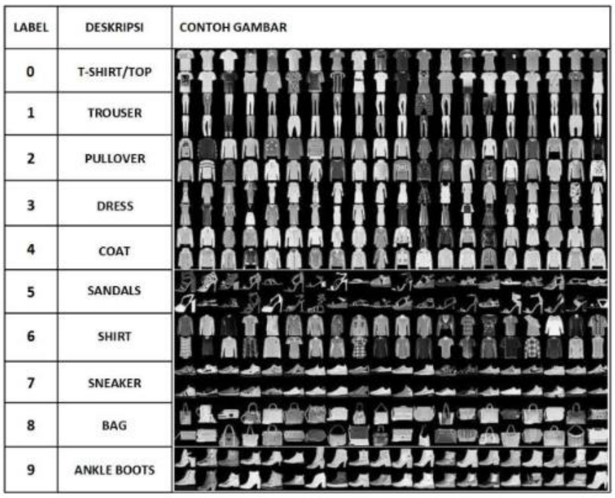

Figure 1. Example of Fashion-MNIST Classification

Image classification is a fairly easy task for humans, but for machines, it is easy to do something very complex and a big problem. But classifying lots of images, would be tedious. Moreover, humans are very likely to make mistakes in blurry images. Therefore, it would be very useful if we could automate this entire process using Computer Vision [7]. In computer vision, object classification or recognition is one of the popular applications [8]. By classifying images, we can help the fashion industry to separate categories and types of various fashion. The goal of classification is to extract features from images and then classify them into each different class category using one of the classification methods [9].

Convolutional Neural Networks (CNN) have made significant progress in image classification, object detection, and more. This is in line with research from x which states that in deep learning, CNN is the most commonly applied method for analyzing visual images [10]. CNN adopted the way of working from the artificial structure of human brain neurons. CNN can do it extraction of features from images in more detail. With the concept of weight and bias, CNN can accept image input with more general characteristics or even with a lot of noise. CNN is a deep learning method that has many architecture models [11]. There are several models in CNN including MobileNetV1, MobileNetV2, ShuffleNet, ShuffleNetV2, Mobie NasNet (MnasNet), and others. And according to Tan et al, MnasNet is the model with the best accuracy for image classification [12].

Therefore, in this research, researchers used the MnasNet classification system as a CNN architectural model. The MnasNet model is 1.8× faster if we compare it with MobileNetV2. Then MnasNet is 2.3× faster than NASNet [13]. Then, if MnasNet is compared with the widely used ResNet-50, the MnasNet model achieves higher accuracy [14]. Based on the background that we have described, we focus on research in the field of image classification using a deep learning approach, namely CNN with the MnasNet architectural model to classify the Fashion-MNIST dataset. Then the following are the research questions in this study based on the existing literature review, including how to implement classification using the MnasNet model, and what are the results of classification accuracy using the MnasNet model.

2. LITERATURE REVIEW

In this chapter, researchers will conduct a literature review in international journals and national journals related to the determined research topic. This literature review aims to find sources of information and study and analyze image classification and deep learning models, namely CNN with the MnasNet architectural model. This chapter also functions to solve problems and find solutions to the problems that have been described in the research background. Related works related to image classification are in Table 1, and related works related to the deep learning approach are in Table 2.

Table 1. Related works to image classification

References	Approaches	Steps	Results
Jiang [15]	Visual Geometric Group (VGG) 16	Data pre-processing, CNN network training, data augmentation, results	The accuracy of the VGG model is 89.1%, precision is 79.5%, recall is 99.0%, and F1-Measure is 88.2%
Çinar [16]	Improved hybrid model, Dense Convolutional Netrwork (DenseNet) 201 model, Residual Network	Collect dataset, deep learning such as input layer, activation function, convolution layer,	Classification results of the all models is 97.12%, but the others model get low accuracy.

References	Approaches	Steps	Results
	(ResNet) 50 model, InceptionV3 model, GoogleNet model, and AlexNet model	normalization, dropout, fully connected layer, pooling layer, softmax, classification	DenseNet201 get 96.83%, ResNet50 get 96.35%, Inceptionv3 get 95.35%, GoogleNet get 94.055, and AlexNet get 91.07%.
Saraiva [17]	CNN	Description of the dataset, input structure for learning model, training structure, proposed model CNN	The average accuracy of this paper get high accuracy around 95.30%
Kapila [18]	CNN	Dataset collection and description, preprocessing, tumor classiication using CNN, performance evaluation	This research achieve a loss of 28.16% and an accuracy of 94.39%
Paul [19]	Fully connected and convolutional neural networks	Collecting dataset, preprocessing include vanilla data preprocessing, tumor location, and tumor zoom, then do image augmentation, counteracting overfitting, network construction, random forest, training, dan evaluating	The result of this research has proven to be accurate in its classification with average of 91.43% on the best neural network
Sarwinda [20]	ResNet	Collecting material, research method, image processing, deep learning model using ResNet, stochastics gradient descents with momentum, performance evaluation	In this study, ResNet-50 had higher accuracy than ResNet-18. This research produced accuracy between 73%-88% and sensitivity values between 64%-96%.

Table 2. The related works to deep learning approach: CNN

References	Method	Process	Result
Hameed [21]	VGG16 and VGG19 architectures	Data collection, preprocessing, training, data augmentation, proposed ensemble approach, implementation, evaluation metrics	Improved VGG16 and VGG19 models resulting in sensitivity of 97.73%, accuracy of 95.29%. Also produces an F1 score of 95.29%.
Chaganti [22]	SVM and CNN	Digital data, preprocessing, decision and classification, and accuracy assessment	In this research, the SVM method gets an accuracy of 82%, and CNN of 93.57%
Shah [23]	A-MnasNet	Data collecting, optimization, data augmentation	This research obtained validation accuracy of 96.89% and the model size was 11.6 MB. Then we got 80.8% accuracy with a model size of 12.7 MB
Tan [24]	MnasNet	Data collection, training, evaluation	Experimental results show that ImageNet, MnasNet achieves 75.2% accuracy with 78 ms latency on Pixel phones, where ImageNet is 1.8x faster than MobileNetV2. MobileNetV2 has 0.5% higher accuracy and is 2.3x faster than NASNet. And NASNet has 1.2% higher accuracy. MnasNet achieves better map quality than MobileNets for COCO object detection
Aghera [25]	CNN with 5 architecture: MobiExpressNet, Low complexity model, MobileNetV2+SSD, CNN based+face extraction, EdgeCNN, MnasNet based lightweight CNN	Data collection, training, evaluation	The highest accuracy is Mnasnet. MnasNet model achieved an accuracy of 70.82%
Lei [26]	CNN and HDC	Data collection, training dan testing of dilated CNN model, training and testing HDC model, comparation	The dilated CNN model improves the training accuracy by 2.86% averagely, the HDC model improves the training and testing accuracy by 14.15% and 15.35% averagely

3. THEORY AND METHODS

In this session researchers will use the MnasNet architectural model. Researchers will explain the theory and methods. Section 3.1 is an explanation of deep learning and section 3.2 is an explanation to fully understand the MnasNet architectural model which is part of the deep learning approach that will be carried out for this research.

3.1. Deep learning

Deep Learning is a techniques in machine learning that can process nonlinear information with uses multiple layers to perform pattern identification, feature extraction and classification which is a method of studying representations that allow models computational calculations consist of many layers of processing by studying the data from many levels of abstraction [27]. This is in line with research conducted by Aryanto et al that deep learning is a branch of machine learning that uses algorithms inspired by the structure of the human brain [28]. The key aspects of deep learning are feature layers are not designed by humans, they are learn data using general purpose learning procedures. Deep learning is making great progress in solving problem [29]. Figure 3.1 is the structure where deep learning is located.

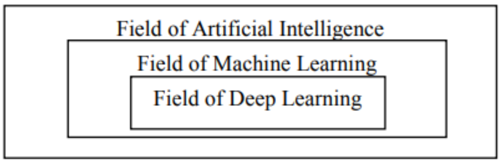

Figure 2. Field of deep learning

Deep learning refers to deep artificial neural networks. Deep is a term that refers to the number of neural network layers. And deep networks have more than one hidden layer while shallow networks only have one [30]. Likewise, according to Shinde et al, deep learning is part of machine learning. Deep learning uses neural networks. So deep learning can also be called deep neural network. The types of deep learning are Autoencoder (AE), Deep Belief Network (DBN), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Recursive Neural Network and Direct Deep Reinforcement Learning. Figure 3 is an image of deep learning applications.

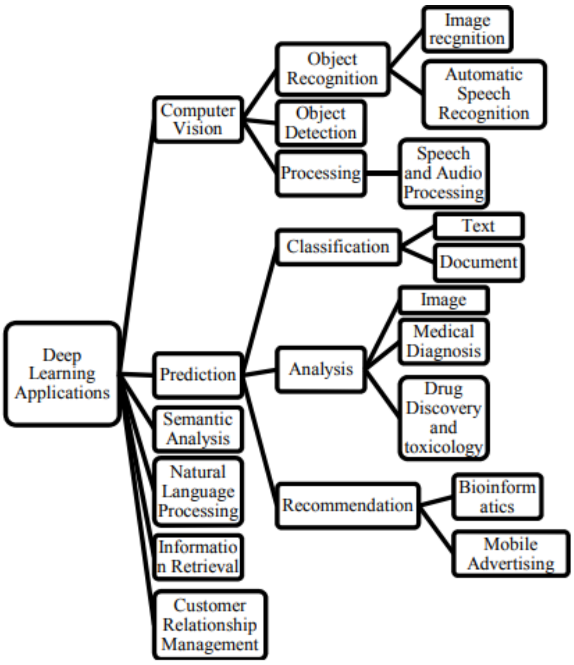

Figure 3. Deep learning applications

3.2. MnasNet

MnasNet is an aware neural network platform for mobile. Machine learning models can take a lot of time and effort. This model is very helpful because the search space can be very large because MnasNet is a deep learning approach. MnasNet is designed using reinforcement learning. The goal is to let the neural architecture find a model that not only achieves good accuracy, but also reduces delay in training. This model has three components, namely RNN based controller, trainer, and inference engine. The RNN based controller learns and samples the architecture, the trainer trains the model, and the inference engine to measure speed on the mobile platform. MnasNet is an architectural model of CNN, so CNN is factored into a sequence of blocks. Then the model uses hierarchical search space to determine the appropriate architect for each block [25]. According to Aghera, MnasNet is 1.5x faster than MobileNetV2, and 2.4x faster than NASNET. MnasNet provides much greater accuracy than MobileNet. In general, MnasNet provides better accuracy when compared to various other mobile models. This is in line with one study which states that MnasNet is a CNN architecture designed for mobile devices with limited computing power [24]. According to Tan, MnasNet also outperforms MobileNetV2 in ImageNet classification and COCO detection. MnasNet works 1.5x faster. The computational costs and parameters can be easily implemented to overcome the existing problem [31]. Figure 4 is Imagenet Top 1 Accuracy (%) between MnasNet and MobileNetV2.

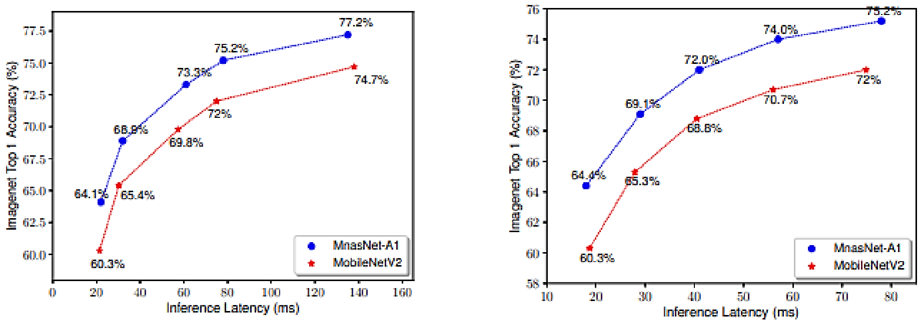

Figure 4. MnasNet vs MobileNetV2

It can be seen that the percentage of MnasNet is far above MobileNetV2. And Figure 5 is the architecture of the MnasNet model.

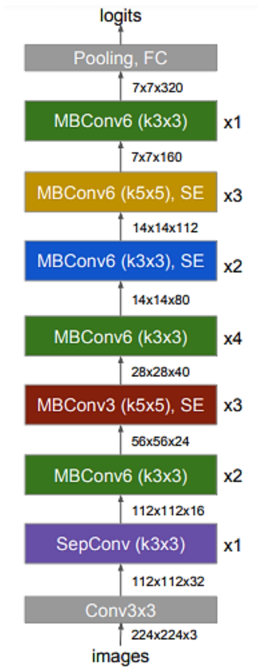

Figure 5. MnasNet Architecture

Figure 5 illustrates the MnasNet model. It can be seen that the model consists of various layer architectures throughout the network. MnasNet uses both 3x3 and 5x5 convolutions which is different from other mobile models which only use 3x3 convolutions.

4. RESEARCH MEHODOLOGY

We created the framework below in the form of a flowchart so that it is hoped that it can solve the research problems described previously. In Figure 6, the steps taken are a literature review using international journals and national journals, identifying problems, collecting datasets, exploring existing datasets and describing them, then conducting experiments by training datasets and evaluating by testing datasets using a deep learning approach, namely MnasNet.

From everything we have done, after evaluation, there are accuracy results from image classification using MnasNet. With that, the existing problems have been solved and the research objectives have been achieved.

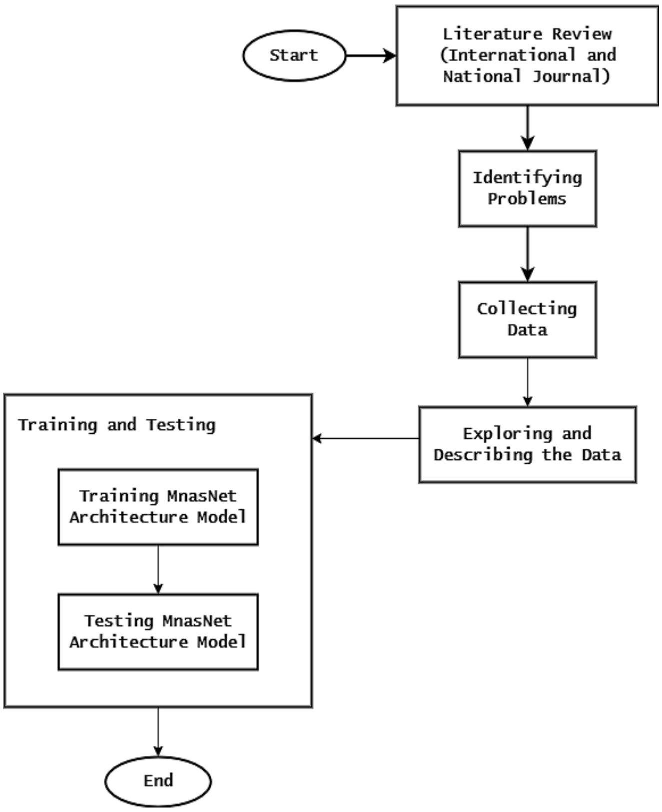

Figure 6. Research Methodology - Framework

4.1. Collecting Data

The step that must be taken after identifying the problem is to search for a dataset. The name of the dataset is Fashion MNIST. The dataset is divided into 10 classes, namely:

1. Ankle Boot
2. Bag
3. Sneaker
4. Shirt
5. Sandal
6. Coat
7. Dress
8. Pullover
9. Trouser, and
10. T-shirt/top.

4.2. Exploring and Describing Data

In this step, we explore the data that was obtained at the collecting dataset stage. The goal is to understand data before it is analyzed. This needs to be done by every researcher so that the information can be analyzed correctly. We find out the image type, image shape, and also the shape label. Then after that we did describing the data and also preprocessing the data. We also split the data.

4.3. Training with MnasNet

Then we try to training the dataset using the MnasNet architectural model. And the following is the model summary output:

```
Model: "model"
__________________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
==================================================================================================
input_5 (InputLayer)            [(None, 224, 224, 3) 0
__________________________________________________________________________________________________
conv2d_8 (Conv2D)               (None, 112, 112, 32) 864         input_5[0][0]
__________________________________________________________________________________________________
batch_normalization_12 (BatchNo (None, 112, 112, 32) 128         conv2d_8[0][0]
__________________________________________________________________________________________________
re_lu_12 (ReLU)                 (None, 112, 112, 32) 0           batch_normalization_12[0][0]
__________________________________________________________________________________________________
depthwise_conv2d_4 (DepthwiseCo (None, 112, 112, 32) 288         re_lu_12[0][0]
__________________________________________________________________________________________________
batch_normalization_13 (BatchNo (None, 112, 112, 32) 128         depthwise_conv2d_4[0][0]
__________________________________________________________________________________________________
re_lu_13 (ReLU)                 (None, 112, 112, 32) 0           batch_normalization_13[0][0]
__________________________________________________________________________________________________
conv2d_9 (Conv2D)               (None, 112, 112, 16) 512         re_lu_13[0][0]
__________________________________________________________________________________________________
batch_normalization_14 (BatchNo (None, 112, 112, 16) 64          conv2d_9[0][0]
__________________________________________________________________________________________________
re_lu_14 (ReLU)                 (None, 112, 112, 16) 0           batch_normalization_14[0][0]
__________________________________________________________________________________________________
conv2d_10 (Conv2D)              (None, 112, 112, 48) 768         re_lu_14[0][0]
__________________________________________________________________________________________________
batch_normalization_15 (BatchNo (None, 112, 112, 48) 192         conv2d_10[0][0]
__________________________________________________________________________________________________
re_lu_15 (ReLU)                 (None, 112, 112, 48) 0           batch_normalization_15[0][0]
```

Figure 7. Output Model Summary

4.4. Testing the Model

On this session, we evaluate the model that has undergone preprocessing and training. The results will be explained in Part 5, namely Results and Analysis.

5. RESULTS AND ANALYSIS

5.1. Collecting Dataset

The dataset used in this research contains Fashion Images in the form of Ankle Boot, Bag, Sneaker, Shirt, Sandal, Coat, Dress, Pullover, Trouser, and T-shirt/top. The MNIST Fashion dataset can be accessed using torchvision. The image shape is ([64, 1, 28, 28]), and the size is 64. There are 70,000 data where for training, we use 60,000 data and for testing, we use 10,000 data.

5.2. Results and Analysis the Model

Results and analysis can be seen in Table 3. Table 3 will show the loss and accuracy results of the trained model. There is also information regarding total parameters, trainable parameters, and non-trainable parameters.

Table 3. Results for the model

Detail	Result
Total Params	4,251,184
Trainable Params	4,213,520
Non-trainable Params	37,664
Loss	0.4426
Accuracy	0.8991

It can be seen that image classification using MnasNet with Fashion MNIST data which can be accessed via torchvision and using several parameters, can produce an accuracy of 0.8991 or 89%, and a loss of 0.4426. Based on the results of this research, it can be concluded that the results are good. Because we can achieve the goal, namely classifying blurry images into the appropriate class. Here is an example fig 8 and 9.

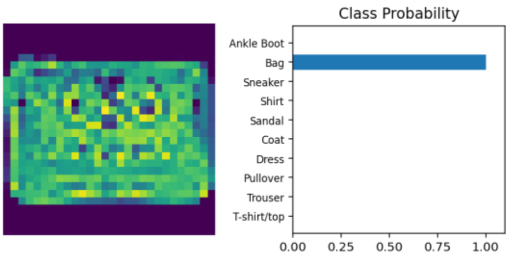

Figure 8. Output Predicted Blur Image – Bag

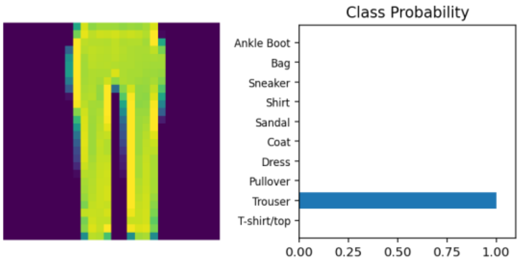

Figure 9. Output Predicted Blur Image - Trouser

It can be seen that the model can classify blur images correctly.

6. CONCLUSION

This research uses the MnasNet architectural model. The framework used is identifying problems, conducting literature reviews in international and national journals, conducting training and also testing. Data is divided into two, namely training data and testing data. Training data is 60,000 and testing data is 10,000. MNIST Fashion data can be accessed via torchvision. The accuracy result is 89%, and the loss is 0.4426 using MnasNet as the architectural model. With this, it can be concluded that image classification on blur images is very suitable when using the MnasNet architectural model, especially datasets in the Fashion sector.

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Rani Puspita is a lecturer School of Computer Science at Bina Nusantara University. Focus on artificial intelligence, multimedia technology and software engineering. Her undergraduate education background is Informatics Engineering at Syarif Hidayatullah State Islamic University Jakarta and her graduate education background is Computer Science at Bina Nusantara University. She is the Best Graduate of Informatics Engineering Major at Syarif Hidayatullah State Islamic University Jakarta (115th Graduation). And she received Summa Cum Laude of Master of Computer Science at Binus University (65th Graduation). She can be contacted via email: rani.puspita@binus.ac.id.

Zahra Nabila Izdihar is a lecturer at Bina Nusantara University (School of Computer Science). Her undergraduate education background is Informatics Engineering at State University of Malang and her graduate education background is Computer Science at Bina Nusantara University. Focus on Data science, Artificial Intelligence, Deep learning, and Machine Learning. She can be contacted via email: zahra.izdihar@binus.ac.id.