# A DEEP LEARNING-BASED METHOD FOR BLUR IMAGE CLASSIFICATION USING DENSENET-121 ARCHITECTURE

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**ABSTRACT**

Blur image classification is essential for computer vision applications, including image quality assessment, surveillance and medical imaging systems. This study proposes a method to classify different types of blur: sharp, Gaussian blur, motion blur, and defocus blur, using the DenseNet-121 architecture. The approach leverages densely connected convolutional layers of DenseNet-121 for efficient, multi-scale feature extraction critical for distinguishing blur types. Data augmentation was applied to create diverse blur patterns, and the model was fine-tuned on a specialized dataset for robust performance. Transition layers and a global average pooling layer with a softmax classifier were incorporated to optimize feature management and output class probabilities. Experiments demonstrated that this method achieves a high accuracy rate of 97.8%, outperforming baseline models in blur classification. Overall, the DenseNet-121-based approach significantly enhanced classification accuracy and provides a scalable, effective solution for real-world image processing tasks that required precise blur detection.

# PHƯƠNG PHÁP DỰA TRÊN HỌC SÂU TRONG PHÂN LOẠI HÌNH ẢNH MỜ SỬ DỤNG KIẾN TRÚC DENSENET-121

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**TỪ KHÓA**

Phân loại ảnh mờ
Kiến trúc DenseNet-121
Đánh giá chất lượng hình ảnh
Tăng cường dữ liệu
Thị giác máy tính

**TÓM TẮT**

Phân loại ảnh mờ đóng vai trò quan trọng trong các ứng dụng thị giác máy tính, bao gồm các hệ thống đánh giá chất lượng hình ảnh, giám sát và hình ảnh y tế. Nghiên cứu này đề xuất một phương pháp để phân loại các loại mờ khác nhau: ảnh sắc nét, mờ Gaussian, mờ chuyển động và mờ do mất nét, bằng cách sử dụng kiến trúc DenseNet-121. Phương pháp này khai thác các lớp tích chập kết nối dày đặc của DenseNet-121 để trích xuất đặc trưng nhiều mức một cách hiệu quả, điều này rất quan trọng cho việc phân biệt các loại mờ. Kỹ thuật tăng cường dữ liệu cũng được áp dụng để tạo ra các mẫu mờ đa dạng, và mô hình được tinh chỉnh trên một tập dữ liệu chuyên biệt để đảm bảo đạt hiệu suất cao. Các lớp chuyển tiếp và lớp *global average pooling* với bộ phân lớp *softmax* được tích hợp để tối ưu hóa quản lý đặc trưng và đưa ra xác suất phân lớp. Thực nghiệm cho thấy phương pháp này đạt độ chính xác cao (97,8%), tốt hơn so với các mô hình cơ bản khác trong phân loại ảnh mờ. Nhìn chung, phương pháp dựa trên DenseNet-121 này cải thiện đáng kể độ chính xác phân loại và cung cấp một giải pháp hiệu quả, có khả năng mở rộng cho các tác vụ xử lý ảnh yêu cầu nhận diện mờ chính xác.

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## 1. Introduction

Blur image classification plays a crucial role in numerous applications, including image restoration, quality assessment, and object recognition. In image restoration, accurately classifying the type of blur can significantly enhance the quality of deblurring algorithms by allowing for tailored restoration approaches. Similarly, in image quality assessment, classifying blurred images aids in determining the sharpness and usability of images across fields like photography, medical imaging, and remote sensing. In object recognition, understanding the nature and extent of blur in an image can improve the accuracy of object detection and classification models, particularly in environments with challenging visual conditions.

Despite its importance, blur image classification presents unique challenges due to the loss of critical visual details that blur introduces. Blurred images often lack the well-defined edges and textures that are vital for many traditional classification methods. Different types of blur—such as motion blur, Gaussian blur, and defocus blur—can vary significantly in appearance, further complicating classification tasks. Consequently, developing effective methods for accurately distinguishing these blur types is essential to improve performance in related applications.

Traditional blur classification methods often rely on handcrafted features and signal processing techniques, which can be limited in their ability to generalize across different blur types or to adapt to real-world variations. These approaches may struggle to accurately classify blurs under varied lighting, noise, or resolution conditions and typically require domain-specific knowledge to extract relevant features effectively. In contrast, deep learning methods, particularly convolutional neural networks (CNNs), have demonstrated strong capabilities in automatic feature extraction and classification across diverse and complex datasets. Leveraging these advantages, deep learning models present a promising avenue for more robust and adaptable blur classification.

Several approaches have been proposed to detect and classify different types of blur, including defocus, Gaussian, motion, and haze blur. Convolutional Neural Networks (CNNs) have shown promising results in this field, with simplified and ensemble models outperforming traditional methods [1], [2]. These deep learning approaches can accurately classify blur types without requiring image deblurring or blur kernel estimation. Earlier work utilized support vector machines and segmentation techniques to detect and classify blurred regions in images [3], [4]. Another approach examined singular value information and alpha channel constraints to detect and classify motion and defocus blur [5]. Recent advancements include the creation of large-scale blur image datasets and the development of ensemble CNN models, which have demonstrated superior performance in blur classification tasks [2]. Deep Belief Networks (DBNs) have also been explored for blur type classification and parameter estimation [6]. Some approaches incorporate edge detection techniques to extract features for classification [7]. A two-stage method using a pre-trained deep neural network (DNN) and a general regression neural network (GRNN) has been proposed for blur type classification and parameter estimation [8]. These deep learning methods have demonstrated superior performance compared to traditional approaches, even for non-uniformly blurred images, and have been tested on standard datasets such as Berkeley and Pascal VOC 2007 [8], [9].

DenseNet-based models have been particularly effective, with Densenet-121 achieving high accuracy in related image classification tasks [10]. Modifications to DenseNet, such as incorporating atrous convolution, have improved performance in motion deblurring [11]. Studies have emphasized the importance of high-level semantic information in blur detection [12] and explored the impact of blur on classification accuracy [13]. To enhance blur classification, researchers have proposed ensemble CNN approaches [2] and investigated the use of deblurring algorithms like Lucy-Richardson-Rosen to improve deep learning network performance [14]. These advancements contribute to more robust image processing and computer vision applications.

This paper aims to explore the application of a deep learning-based approach using DenseNet-121 for the classification of blurred images. By utilizing DenseNet-121 as the core architecture for classifying various blur types (e.g., motion blur, Gaussian blur, defocus blur, and sharp images), we aim to contribute a novel method to the field of blur image classification and demonstrate the potential of deep learning approaches in addressing the complexities associated with blurred image data.

## 2. Methodology

### *2.1. Image Blur Modeling*

*2.1.1. Mathematical Formulation*

The blur model operates under the assumption that a degraded or blurred image $B$ is generated by the convolution of an ideal (i.e., sharp and unblurred) image $I$ with a point spread function (PSF) $K$ [15]. This relationship can be expressed as:

$$B(x,y) = (I \otimes K)(x,y) + N(x,y) \qquad (1)$$

where $B(x,y)$ represents the observed blurred image at pixel location $(x,y)$; $I(x,y)$ denotes the original, undistorted image; $K(x,y)$ is the blur kernel or PSF, describing how each point in $I$ is spread across neighboring pixels; $N(x,y)$ is an additive noise term, accounting for additional distortions caused by environmental or sensor noise, and $\otimes$ represents the convolution operation over spatial coordinates. This model is illustrated in Figure 1.

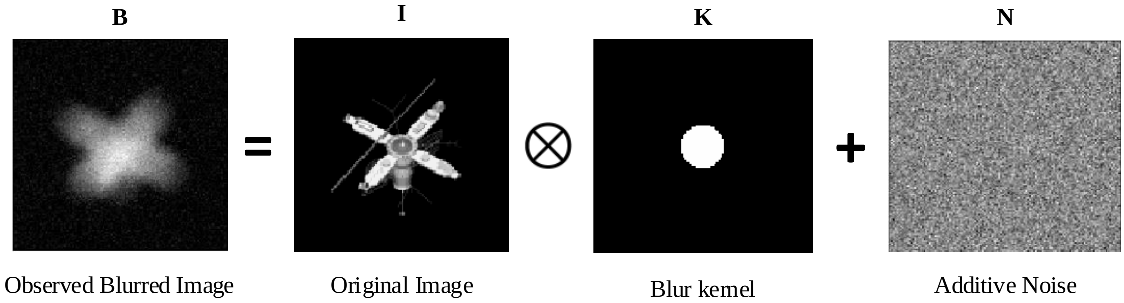



**Figure 1**. *Blurred image formation with blur kernel and additive noise*

This convolution-based model is particularly effective for linear and spatially invariant blur, where the PSF remains consistent across the image. In cases of more complex, non-linear blurs, adaptations to the model are required.

*2.1.2. Types of Blur Kernels*

The properties and shapes of blur kernels vary based on the cause of the blur—whether due to optical limitations, object motion, camera movement, or focus depth. Figure 2 illustrates different blur effects from the same sharp image. Here, we explore some of the most commonly used blur kernels and their distinct.

*Gaussian Blur:* The Gaussian blur kernel models image blur caused by defocusing or other factors that distribute light across the sensor in a bell-shaped spread. This kernel is isotropic, meaning it spreads uniformly in all directions, and is defined by a Gaussian function [9]:

$$K(x,y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2+y^2}{2\sigma^2}\right) \qquad (2)$$

where $x$ and $y$ are the pixel coordinates relative to the center of the kernel; σ the standard deviation, controlling the spread of the blur. The Gaussian kernel is highly versatile due to its smooth, continuous nature and is effective for simulating natural defocus effects. Increasing $\sigma$ leads to a stronger blur, effectively simulating greater out-of-focus effects. Gaussian blur is frequently used for reducing noise, smoothing images, and in applications where a gentle, uniform blur effect is desired.

*Motion Blur:* Motion blur occurs when either the camera or the object being captured moves during exposure, causing an elongated effect along the direction of motion. This effect can be represented by a linear or directional kernel that spreads intensity along a specified path. A simple 1D motion blur kernel can be expressed as [16]:

$$K(x,y) = \begin{cases} \frac{1}{L} & if\ y = x \operatorname{tang}(\theta) \text{ and } \sqrt{x^2+y^2} \le \frac{L}{2} \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

where $L$ is the length of the blur in pixels, simulating the extent of the motion; $\theta$ is the angle of motion, determining the direction of the blur.

In practice, motion blur kernels can become complex, especially if motion is curved or varies across the image. The kernel can also be extended to capture non-linear paths (e.g., parabolic or circular) if motion occurs in more complex patterns. Motion blur is commonly modeled for deblurring in real-time video processing, photography, and object tracking in computer vision.

*Defocus Blur:* Defocus blur, or aperture blur, typically arises from lens limitations, where points outside the focal plane appear as circular "disks" due to the shape of the lens aperture. This type of blur is represented by a disk-shaped kernel that approximates the physical circular aperture, defined as [17]:

$$K(x,y) = \begin{cases} \frac{1}{\pi R^2} & if\ \sqrt{x^2+y^2} \le R \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

where R is the radius of the disk, determined by the lens aperture and the degree of defocus.

This model captures the circular bokeh effect common in defocused areas in photography, especially when using wide apertures. The disk blur kernel is generally larger for regions further from the focal plane, with greater blur radius resulting in more pronounced out-of-focus effects. The kernels are particularly relevant for simulating depth-of-field effects in photography and are often used in the rendering of 3D images to replicate real-world lens behavior.

Sharp Motion blur Defocused blur Gaussian blur

**Figure 2.** *Examples of different blur types in images*

### *2.2. DenseNet-121 architecture for blur image classification*

The DenseNet-121 architecture [18], a member of the Dense Convolutional Network (DenseNet) family, is a deep convolutional neural network known for its dense connectivity between layers, enabling efficient feature reuse and gradient flow. Unlike traditional convolutional networks, where each layer receives input only from its previous layer, DenseNet-121 establishes connections where each layer receives the outputs from all preceding layers and passes its own feature maps to all subsequent layers within the same dense block. This approach minimizes redundancy and encourages each layer to extract new features, enhancing the capacity of model to learn rich representations while reducing the number of parameters as description in Figure 3.

DenseNet-121 contains 121 layers organized into four dense blocks interspersed with transition layers. Each layer within a dense block produces a set of feature maps, which are concatenated with feature maps from previous layers and forwarded to subsequent layers, forming a collective representation. Mathematically, the output $x_l$ of the $l$-th layer in a dense block can be described as:

$$x_l = H_l([x_0, x_1, \dots, x_{l-1}]) \tag{5}$$

where $H_l$ is a composite function of Batch Normalization (BN), a Rectified Linear Unit (ReLU) activation, and a convolutional operation (typically a $3 \times 3$ convolution), and $[x_0, x_1, \dots, x_{l-1}]$ represents the concatenated outputs of all preceding layers.

To control the complexity of the model and manage computational resources, transition layers are introduced between dense blocks. These layers include $1 \times 1$ convolutions to reduce the number of feature maps, followed by average pooling to decrease spatial resolution. Through this dense connectivity, DenseNet-121 efficiently captures multi-scale features essential for complex image classification tasks.

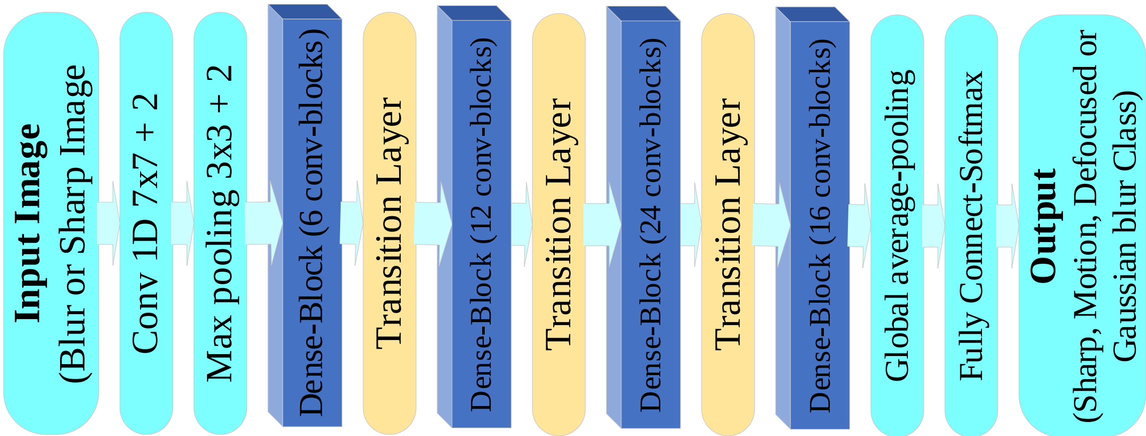



**Figure 3**. *Proposed DenseNet-121 architecture for blur image classification*

DenseNet-121 is particularly well-suited for applications in image classification due to its ability to learn hierarchical and fine-grained patterns, such as textures, edges, and shapes, which are essential for distinguishing subtle differences in image characteristics. Given its ability to reuse features, DenseNet-121 is also more parameter-efficient, making it suitable for tasks with limited computational resources. In our study, this architecture is adapted to classify images by blur type, leveraging its depth and efficient feature reuse to distinguish between Gaussian blur, motion blur, and defocus blur based on subtle texture and edge variations.

*Blur Feature Extraction:* Each convolutional operation within DenseNet-121 applies a filter $K$ to extract relevant features. For blur classification, these filters learn to capture different characteristics of blur. For instance: (1) High-frequency filters detect edges, which differentiate sharp and blurred images; (2) Low-frequency filters capture smooth transitions, distinguishing between Gaussian blur and other blur types.

The output of a convolutional layer at location $(i, j)$ can be expressed as:

$$f(j,j) = \sum_{m=-k}^{k} \sum_{n=-k}^{k} K(m,n) X(i+m, j+n) \tag{6}$$

where $k$ defines the size of the convolution kernel $K$; $X(i+m, j+n)$ is the value of the input at location $(i+m, j+n)$; This operation produces a feature map that highlights edges or blurring characteristics, helping the model recognize blur types.

This model effectively classifies blur types by leveraging dense connections and feature reuse, which allow the model to learn both high- and low-frequency features that distinguish sharpness and different blur patterns. Dense blocks extract multi-scale features, while transition layers control dimensionality, and the final classification layer outputs probabilities for each blur type, trained with cross-entropy loss.

## 3. Experiment results and Analysis

### *3.1. Dataset and Preprocessing*

The training data is blur dataset sourced from Kaggle, containing 1050 images arranged into 350 triplets, with each triplet including: a sharp image; a defocus-blurred image; and a motion-blurred image. The Kaggle Blur dataset is ideal for training and evaluating blur classification methods because it provides a diverse, well-structured, and balanced set of images that represent common blur types in real-world applications. Its easy accessibility, alongside pre-processing and augmentation options, makes it an excellent resource for developing and benchmarking robust image deblurring and blur classification models.

To complete the dataset for all four classes, we generated additional Gaussian-blurred images from each sharp image in the dataset by applying Gaussian filters with varying standard deviations $\sigma$ ranging from 1 to 10, simulating different levels of Gaussian blur. This resulted in four balanced classes (sharp, Gaussian blur, motion blur, defocus blur) with 350 images each. The images were resized to $224 \times 224$ pixels, the input size required by DenseNet-121, and data augmentation techniques were applied to improve model robustness. Augmenting the dataset with varying blur intensities (e.g., Gaussian blur) and spatial transformations (cropping, zooming) enables the model to recognize different levels of blur and spatially varying blur patterns, such as motion blur or defocus blur. These augmentations help the model generalize better to real-world scenarios, where blur can appear in diverse contexts, such as photos with varying lighting, camera movement, or noise. By expanding the dataset and simulating real-world conditions, augmentation prevents overfitting, enhances performance of the model on unseen data, and ensures more accurate classification of blurry images across multiple blur types and conditions.

### *3.2. Model Modifications for Blur Classification*

To adapt DenseNet-121 for the four-class blur classification task, we made the following modifications:

- Replacing the final fully connected layer: The original classification layer of DenseNet-121 was replaced with a fully connected layer containing four neurons, each representing one of the four classes (sharp, Gaussian blur, motion blur, defocus blur).
- Softmax Activation: A softmax function was applied to the output layer to generate a probability distribution across the classes, where the probability $p_c$ of class $c$ is given by:

$$p_c = \frac{\exp(z_c)}{\sum_{j=1}^{4} \exp(z_j)} \quad (7)$$

Here, $z_c$ represents the logit for class $c$, enabling classification based on the highest probability output.

We use a pre-trained DenseNet-121 model from *torchvision models*, modifying the classifier layer to match the number of classes (Sharp, defocused blurred, Gaussian blurred and motion blurred images). Each dense block extracts features by leveraging information from both shallow and deep layers, effectively capturing multi-scale blur patterns, including:

- Sharp edges (distinct features in sharp images),
- Smooth transitions (characteristic of Gaussian blur),
- Directional gradients (common in motion blur),
- Circular patterns (present in defocus blur).

Between dense blocks, transition layers help control the number of features and reduce dimensionality. Each transition layer uses a $1 \times 1$ convolution followed by average pooling:

$$f_{trans} = \text{Pooling}(\sigma(W_{trans}.f)) \tag{8}$$

where $f_{trans}$ is the output of the transition layer; $\sigma$ is is an activation function (ReLU or identity); $W_{trans}$ is the weight matrix of the transition layer; "Pooling" is typically average pooling, which reduces spatial dimensions, helping to retain global blur patterns.

### *3.3. Training process*

The model was initialized with weights pre-trained to take advantage of transfer learning. Training used categorical cross-entropy loss, suitable for multi-class classification, defined for an image $i$ as:

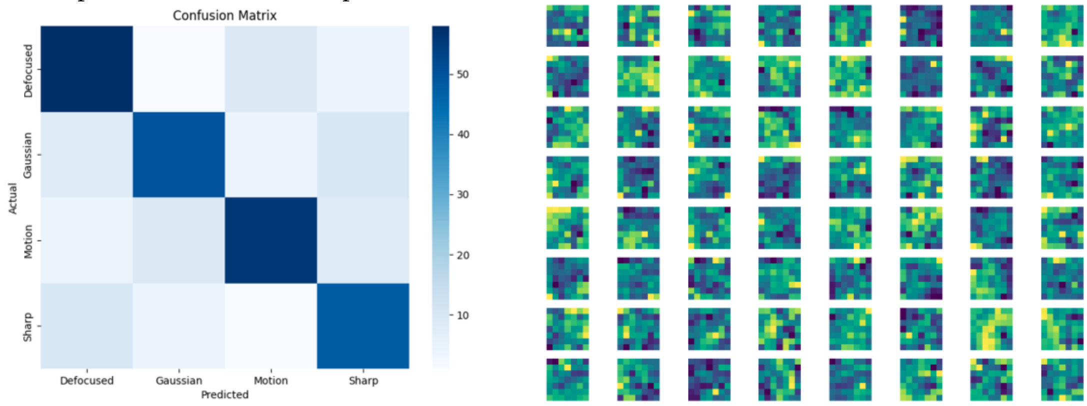
$$L_i = -\sum_{c=1}^{4} y_{i,c} \log(p_{i,c}) \tag{9}$$

where $y_{i,c}$ is the true label (one-hot encoded) and $p_{i,c}$ is the predicted probability for class $c$. The model was optimized using Adam optimizer with a learning rate of $10^{-4}$, reduced upon stagnation in validation loss. A batch size of 32 and early stopping were used to mitigate overfitting.

### *3.4. Result analysis*

*Confusion Matrix:* Figure 4(a) presents the confusion matrix of the trained model. The DenseNet-121 model demonstrates strong performance in classifying blur types, accurately distinguishing between defocused, Gaussian, motion blur, and sharp images. The high values along the diagonal indicate that the model effectively captures distinctive features of each blur type, with only minor misclassifications.

Defocused and sharp images are particularly well-classified, and show that the model reliably differentiates clear and defocused edges. However, there are slight overlaps between Gaussian and motion blur classes, suggesting some similarity in feature representation. Misclassification between Gaussian blur and Motion blur occurs because both blur types create similar softening effects, making it difficult for models to distinguish them. Gaussian blur results in a uniform blur, while motion blur creates directional streaks, but both can blur edges and gradients in similar ways, especially at lower intensities. If the training dataset lacks sufficient variation in blur types or intensity, the model may struggle to differentiate them. Additionally, subtle motion blur or mild Gaussian blur can appear visually similar, leading to misclassification. Data augmentation and better feature extraction can help the model learn these distinctions. To improve accuracy, additional data augmentation focused on blur diversity or incorporating attention mechanisms could help the model focus on specific blur characteristics.

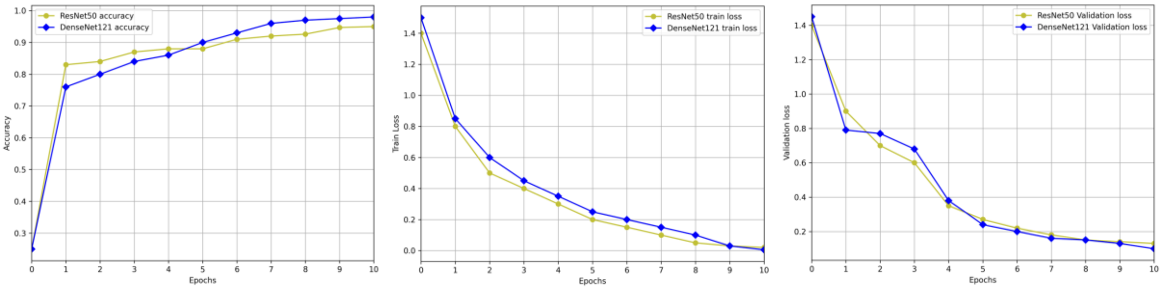



*(a) Confusion Matrix* *(b) Feature Map*

**Figure 4.** *Confusion matrix and feature map of training model*

*Accuracy and Loss Curves:* In Figure 5(a) (accuracy curves), DenseNet-121 achieves a final accuracy of approximately 97.8%, outperforming ResNet-50, which reaches around 95.5%. This highlights the effectiveness of densely connected architecture of DenseNet-121, which enables efficient feature reuse and contributes to superior classification accuracy.

In Figure 5(b) (training loss curves), while ResNet-50 converges faster, reaching a lower training loss of around 0.9 by the 10th epoch compared to 1.15 of DenseNet-121, DenseNet-121 ultimately shows better generalization. This is further supported by Figure 5(c) (validation loss curves), where both models stabilize with similar validation losses close to 0.1, indicating strong generalization capability of DenseNet-121 despite its initially slower convergence.




*(a) Accuracy curves* *(b) Train loss curves* *(c) Validation loss curves*

**Figure 5**. *Loss and Accuracy curves of ResNet50 model and Densenet-121 model*

## 4. Conclusion

This paper introduces a DenseNet-121-based architecture for accurately classifying blur types in images, distinguishing between sharp, Gaussian blur, motion blur, and defocused blur. By leveraging densely connected structure of DenseNet-121, the model effectively captures complex, multi-scale blur features, enhancing classification accuracy. Key components, such as dense blocks with multi-level feature fusion and transition layers for dimensionality reduction, allow the model to process and retain essential blur-related characteristics. Additionally, data augmentation tailored to simulate various blur patterns shows to improve model robustness and generalization. Experimental results indicate that the proposed model achieves superior performance compared to baseline methods, making it suitable for real-world applications in fields like image quality control, medical imaging, and video surveillance. Future work could explore incorporating attention mechanisms and multi-task learning to further refine the ability of model to distinguish subtle differences in blur types. This work lays the foundation for more advanced blur detection techniques, enabling efficient and scalable solutions for diverse computer vision tasks.

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