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1 Introduction

1.1 System overview

Our system is designed to quickly detect fires and sound an alarm before the situation escalates. As the sensors can only work effectively in a closed area, our system is focused on detecting fires in the open area in the mall. To achieve this, we are using cameras and advanced deep-learning techniques to determine if there is a fire present.

1.2 Problem statement

Our primary goal is to detect the presence of a fire, regardless of its location. Therefore, our system focuses on image classification, which involves identifying whether an image contains a fire or not.

One of the most challenging aspects of our system is acquiring a suitable dataset. Our dataset must consist of two classes, fire and normal. However, the "normal" class is challenging to define and acquire. It is essential to ensure that the "normal" images accurately represent the environments in which the system will be used. This is crucial to ensure that the model can distinguish between images that contain a fire and those that do not.

To develop the fire detection system, we can follow the following processes:

1. Search and download suitable data with two classes (Fire and normal)
2. Data preprocessing: Preprocess the data by cleaning and normalizing it
3. Make data augmentation to the dataset
4. Train the state of art models

5. Evaluate the models and choose the best one

2 Methodology

2.1 Data Exploration

To ensure that our fire detection system is effective, we need to include a "normal" class in our dataset that is not biased towards any particular object or environment. This means that we need to include a diverse range of images in the "normal" class, including images with multiple objects in each image.

When collecting data, it's important to prioritize relevant data for our problem. Therefore, we should prioritize collecting normal images over fire images because we don't need the model to identify objects in normal images. Our training objective is to teach the model to recognize fire and output "yes" if it's detected, and "no" otherwise

In this [repository](#) from [Centre for Artificial Intelligence Research \(CAIR\)](#) there are about 700 normal images In addition to some images from another source with a total of 730 images. We collected the fire image from different sources such as CAIR and [FireNET](#), with a total of 706.

To effectively train and evaluate our fire detection model, we will split our dataset into two parts: a training dataset and a validation dataset. We will allocate 80% of the images in the dataset for training the model and 20% of the images for validating the model.



Example of Fire images



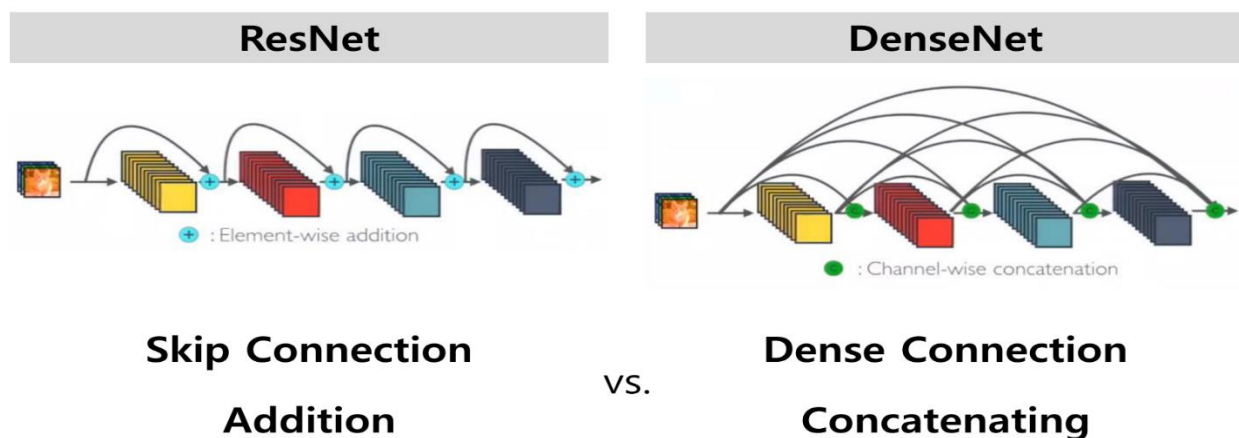
Example of Normal images

2.2 Densenet model

After the big success of the ResNet idea, which involves creating a deeper neural network to learn more complex features without sacrificing the performance and identity of the object, a new architecture called DenseNet was introduced. This updated the ResNet idea with further advancements, resulting in improved accuracy and fewer parameters.

The idea behind ResNet was to add residual connections, which are responsible for preventing the vanishing gradient problem while preserving the identity of the object being classified. These connections are implemented using an element-wise addition operation between the output of a block of layers and the input to the block. This allows the network to learn residual mappings that capture the difference between the input and the output of a block of layers, making it easier to optimize the network and reducing the risk of overfitting. In DenseNet, there is a modification that improves the connectivity between layers by allowing each layer to obtain additional inputs from all previous layers. This is achieved by concatenating the feature maps of all previous layers with the feature map of the current layer.

ResNet vs. DenseNet



Densenet architecture

The architecture consists of dense blocks and transition layers. Each dense block has a fixed number of layers and each layer has an identical number of channels. The output of each layer in a dense block is concatenated with the output of all previous layers in the same block. This creates a dense connectivity pattern between layers, where each layer receives direct input from all previous layers in the same block.

Between each dense block, there is a transition layer that reduces the spatial dimensions of the feature maps using a combination of convolution, pooling, and downsampling. This helps to reduce the computational complexity of the network and control the number of parameters.

The final layer of the network is a global average pooling layer followed by a fully connected layer with softmax activation, which produces the classification probabilities for each class.

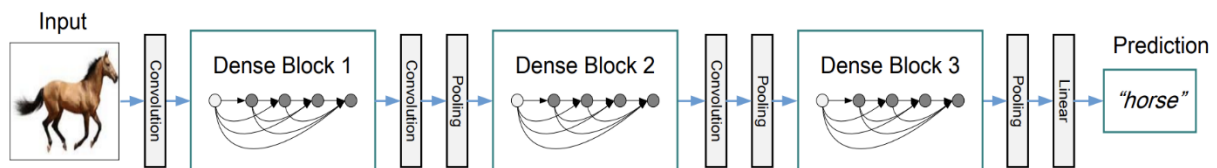


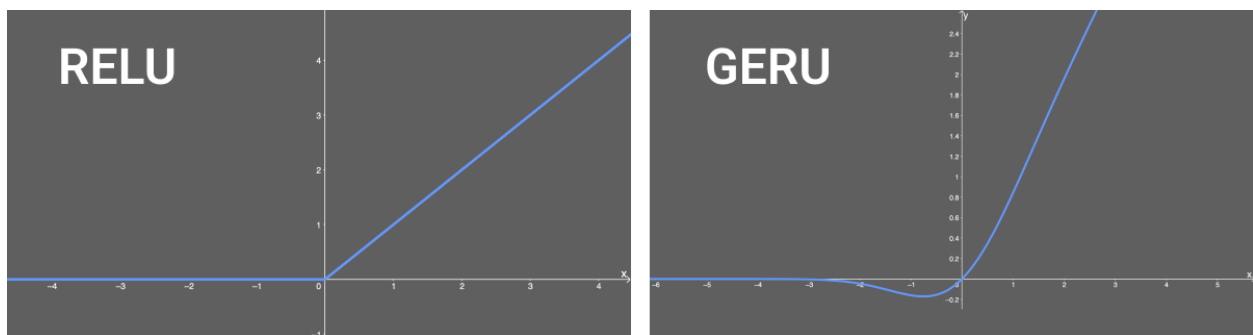
Figure 2: A deep DenseNet with three dense blocks. The layers between two adjacent blocks are referred to as transition layers and change feature-map sizes via convolution and pooling.

2.3 ConvNeXt model

ConvNeXt is considered a new network architecture that was proposed after the high accuracy achieved by the Transformer models in computer vision tasks. The idea behind ConvNeXt is to make some modifications to a traditional CNN architecture, inspired by the vision Transformers.

In the ConvNeXt paper, the authors began by taking the ResNet50 architecture as a starting point and made modifications to both the architecture, the optimizer and apply some heavy data augmentation and regularization.

One of the first changes they made was to replace the Adam optimizer with a new variant called AdamW. This optimizer incorporates weight decay into the optimization process, which helps prevent overfitting and can lead to improved generalization performance.



Replace Relu activation function with its smoother variant Gaussian Error Linear Unit (GERU)

ConvNeXt eliminates some of the normalization layers commonly used in traditional ResNet architectures and replaces the commonly used BatchNorm layer with Normalization Layer.

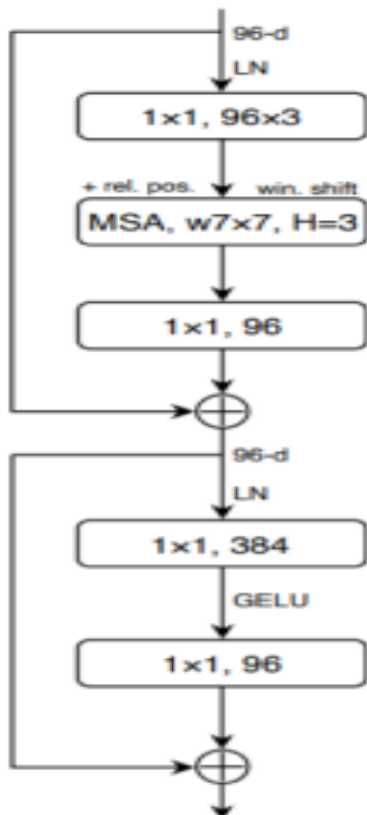
The CnvNeXt architecture consists of a series of building blocks called ConvNeXt modules. Each module consists of multiple parallel pathways, each of which performs a different type of convolution. The output of each pathway is then concatenated and passed through a point-wise convolution to produce the final output of the module.

The different types of convolutions used in ConvNeXt modules are:

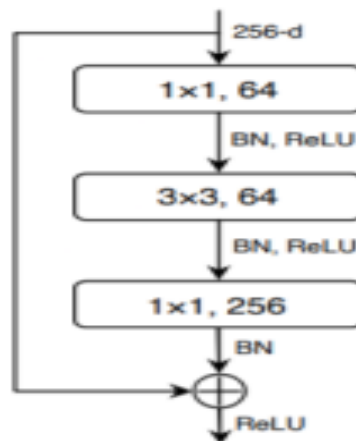
1. Depth-wise convolution: This type of convolution applies a separate filter to each input channel. It is computationally efficient and helps reduce the number of parameters in the network.
2. Point-wise convolution: This type of convolution applies a 1×1 filter to the input channels. It is used to combine information across channels and can help increase the representational power of the network.
3. Grouped convolution: This type of convolution splits the input and output channels into groups and applies a separate filter to each group. It can help reduce the computational cost of convolutions without sacrificing accuracy.

By combining these different types of convolutions in parallel pathways, ConvNeXt can effectively capture both local and global features in the input while maintaining a reasonable computational cost. In addition, the design of ConvNeXt allows for efficient scaling of the network by adding or removing ConvNeXt modules

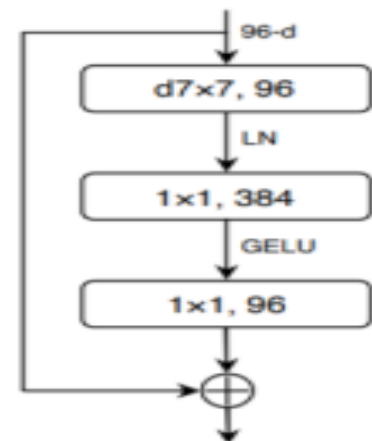
Swin Transformer Block



ResNet Block



ConvNeXt Block



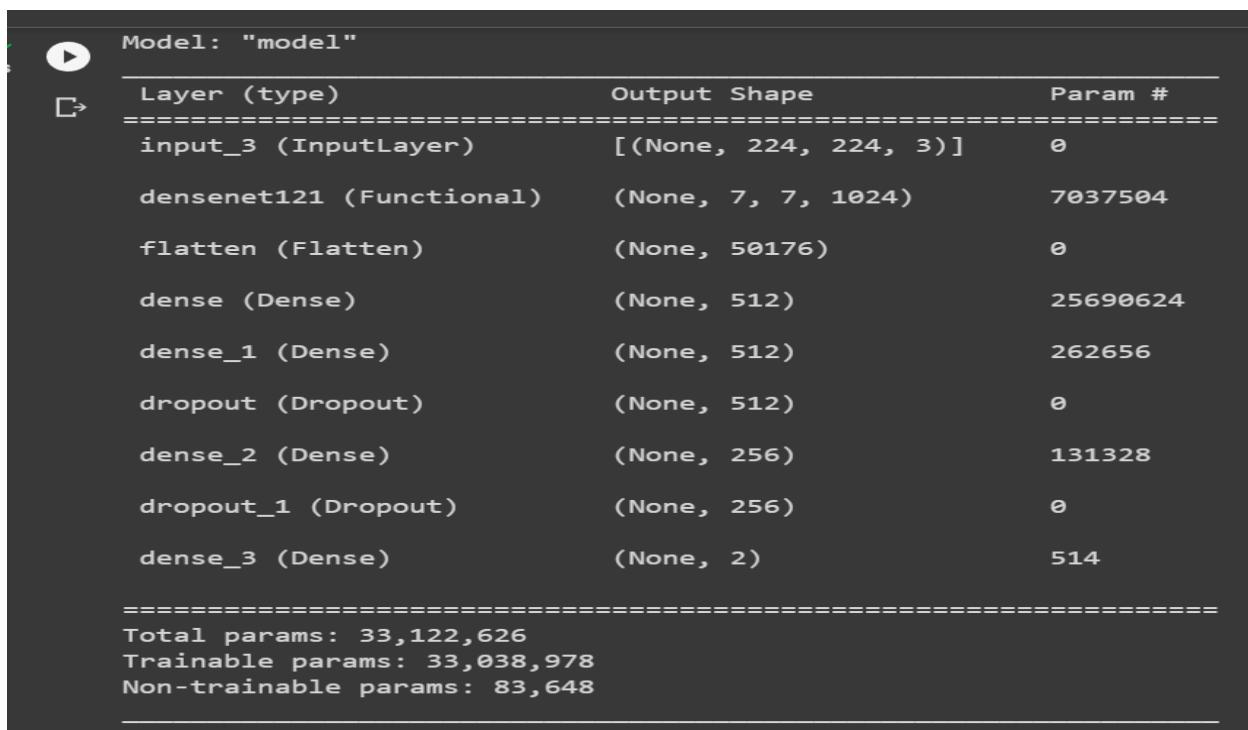
2.4 Training process

We can use several augmentation techniques with the 2 model. Some of these techniques include:

- 1- Rotation range 30
- 2- Zoom range 0.2
- 3- Shear range 0.2
- 4- horizontal_flip
- 5- channel Normalization

DenseNet

The DenseNet model followed by two fully connected layers, each with 512 nodes, a dropout layer with a rate of 0.3, another fully connected layer with 256 nodes, another dropout layer with a rate of 0.3, and a final layer with two output nodes.



Model: "model"

Layer (type)	Output Shape	Param #
input_3 (InputLayer)	[(None, 224, 224, 3)]	0
densenet121 (Functional)	(None, 7, 7, 1024)	7037504
flatten (Flatten)	(None, 50176)	0
dense (Dense)	(None, 512)	25690624
dense_1 (Dense)	(None, 512)	262656
dropout (Dropout)	(None, 512)	0
dense_2 (Dense)	(None, 256)	131328
dropout_1 (Dropout)	(None, 256)	0
dense_3 (Dense)	(None, 2)	514

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Total params: 33,122,626
Trainable params: 33,038,978
Non-trainable params: 83,648

The loss will be categorical_crossentropy with optimizer adam

ConvNext

The ConvNetX model can be followed by a batch normalization layer, a dropout layer with a rate of 0.2, a fully connected layer with 512 nodes and ReLU activation, another batch normalization layer, another dropout layer with a rate of 0.2, and finally a fully connected layer with 2 output nodes.

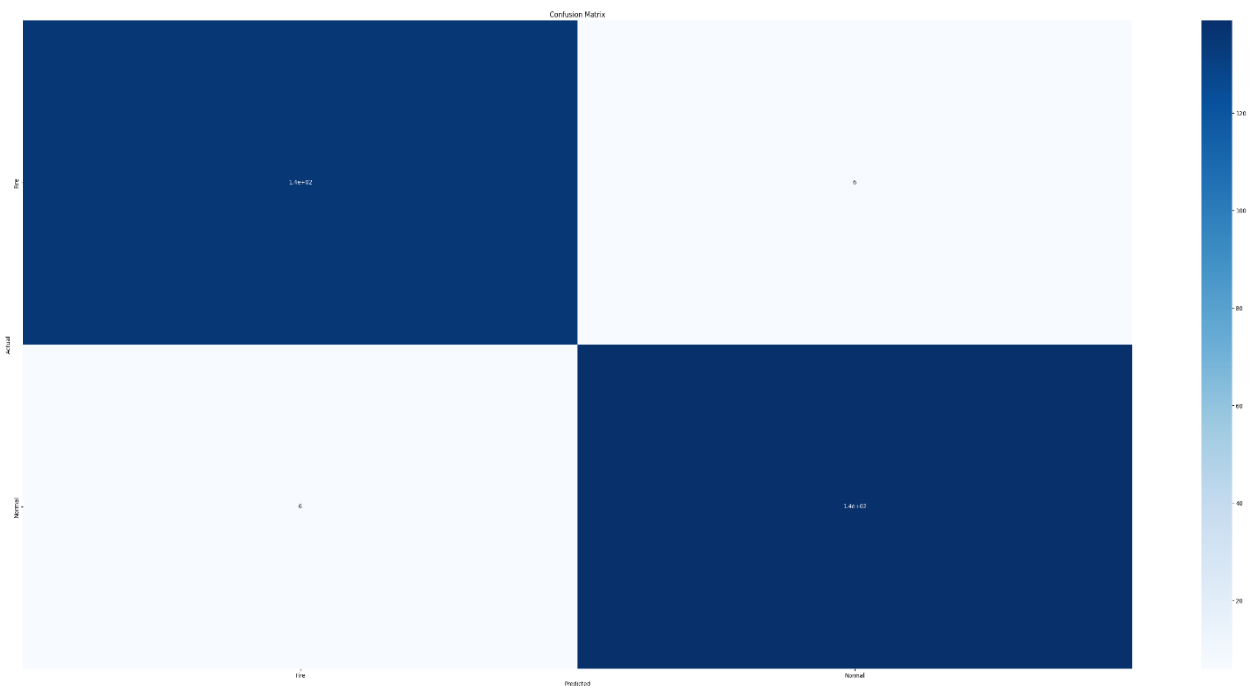
e + Text			
	64 x 2048		
Flatten			
BatchNorm1d		4096	True
Dropout			
	64 x 512		
Linear		1048576	True
ReLU			
BatchNorm1d		1024	True
Dropout			
	64 x 2		
Linear		1024	True
Total params: 88,601,088			
Total trainable params: 88,601,088			
Total non-trainable params: 0			

The loss will be categorical_crossentropy with optimizer adam

3 Results

3.1 DenseNet

After training the DenseNet model for 20 epochs, the model achieved a 0.995 accuracy and 0.0149 loss on the training data and a 0.958 accuracy and 0.1491 loss on the validation dataset.



The confusion matrix indicates that there is no class priority or bias in the classification errors. The errors are distributed equally between the two classes, indicating that the model is not favoring one class over the other.

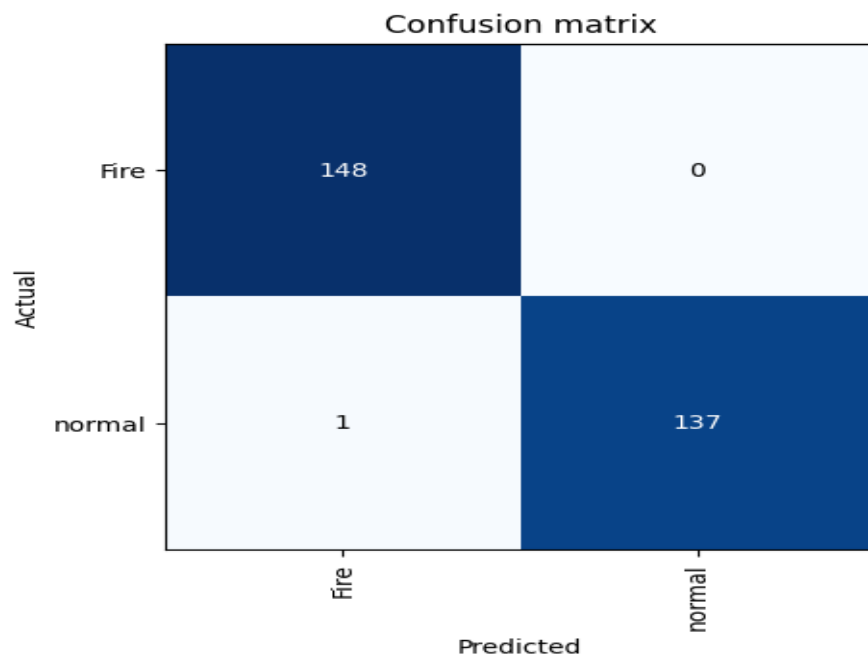
	precision	recall	f1-score	support
Fire	0.957	0.957	0.957	141
Normal	0.959	0.959	0.959	145
accuracy			0.958	286
macro avg	0.958	0.958	0.958	286
weighted avg	0.958	0.958	0.958	286

The current model is performing reasonably well, but there is an issue with some images where the system is incorrectly classifying a non-fire image as a fire or vice

versa. To address this problem, it may be necessary to explore other models and compare their performance to the current model. By evaluating the performance of different models, it may be possible to identify a model that can better distinguish between fire and non-fire images. This can help improve the overall accuracy and reliability of the system.

3.2 ConvNext

After training for 5 epochs, the ConvNetX model is performing very well, achieving an accuracy of 0.993 and a loss of 0.075 on the training dataset, and an accuracy of 0.9965 and a loss of 0.030 on the validation dataset. These results suggest that the model is learning effectively and is able to generalize well to new, unseen data. However, it is important to continue monitoring the performance of the model and evaluate its performance on a test dataset to ensure that it is able to perform well in real-world scenarios.



The model has one misclassification, which is a False Positive, indicating that the model may raise an alarm when there is no fire. This type of error has a low cost, as the model is supervised by a human who can cancel the alarm if it is a false positive. The false positive rate is also very low, less than 0.1 percent, which suggests that the model is performing well overall

	precision	recall	f1-score	support
0	0.993	1.000	0.997	148
1	1.000	0.993	0.996	138
accuracy			0.997	286
macro avg	0.997	0.996	0.996	286
weighted avg	0.997	0.997	0.997	286

Based on the good performance of the ConvNetX model on the validation dataset, we plan to use this model in production. The input size for the model will be set to 224, which is the size that the model was trained on. This will ensure that the input images are properly processed by the model and improve the accuracy of the predictions. Before deploying the model in production, it is important to thoroughly test and evaluate its performance to ensure that it meets the desired level of accuracy and reliability.

4 Conclusion

In conclusion, we have developed and trained a fire classification model using the ConvNetX and DenseNet architecture. The model was trained on a dataset of fire and non-fire images and achieved high accuracy and low loss on both the training and validation datasets. We used several techniques to improve the performance of the model, including data augmentation, batch normalization, and dropout regularization. The model was evaluated on a test dataset and was found to have a low false positive rate, indicating that it is suitable for use in production with a human supervisor to address any false alarms. Overall, the model is accurate, reliable, and effective for classifying fire and non-fire images.