



# E. Material Recognition

CX4042 – Deep Learning & Neural Networks

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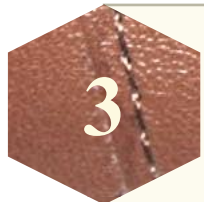
# Agenda



**Context**



**Data Processing**



**Models**



**Data Augmentation**



**Masks**



**Results**






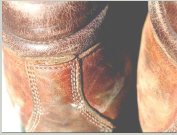
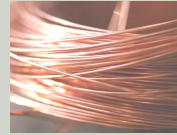



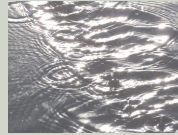

**Garbage Classification**



**Key Takeaways**

# Introduction

## Classify Materials from Image

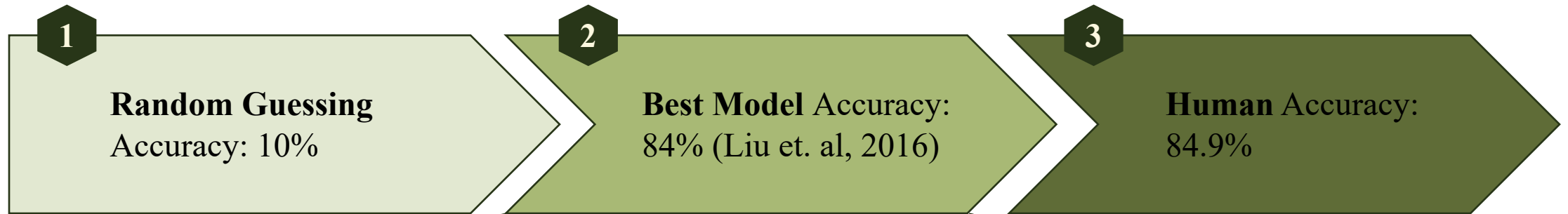
Fabric	Foliage	Glass	Leather	Metal	Paper	Plastic	Stone	Water	Wood
									

### Flickr Material Database:

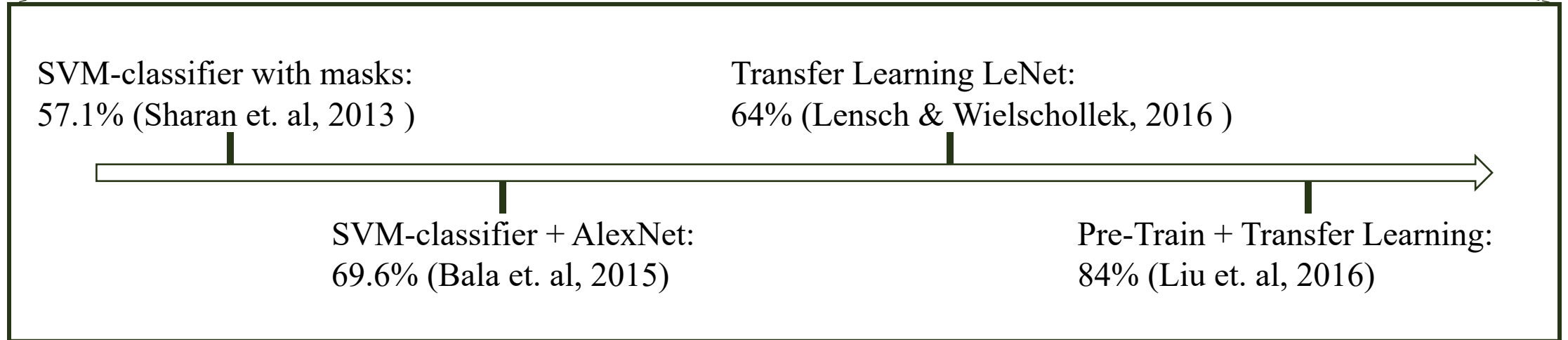
10 categories & 100 images / category

- 500 close-up images
- 500 full object images






# Related Work



## Notable Models:



# Data Preprocessing

 fabric\_object\_048\_new.jpg  
 fabric\_object\_049\_new.jpg  
 fabric\_object\_050\_new.jpg  
 normalizelImage.asv  
 normalizelImage.m

**1. Remove Non *.JPG* Files**



**2. Remove Grayscale Images**

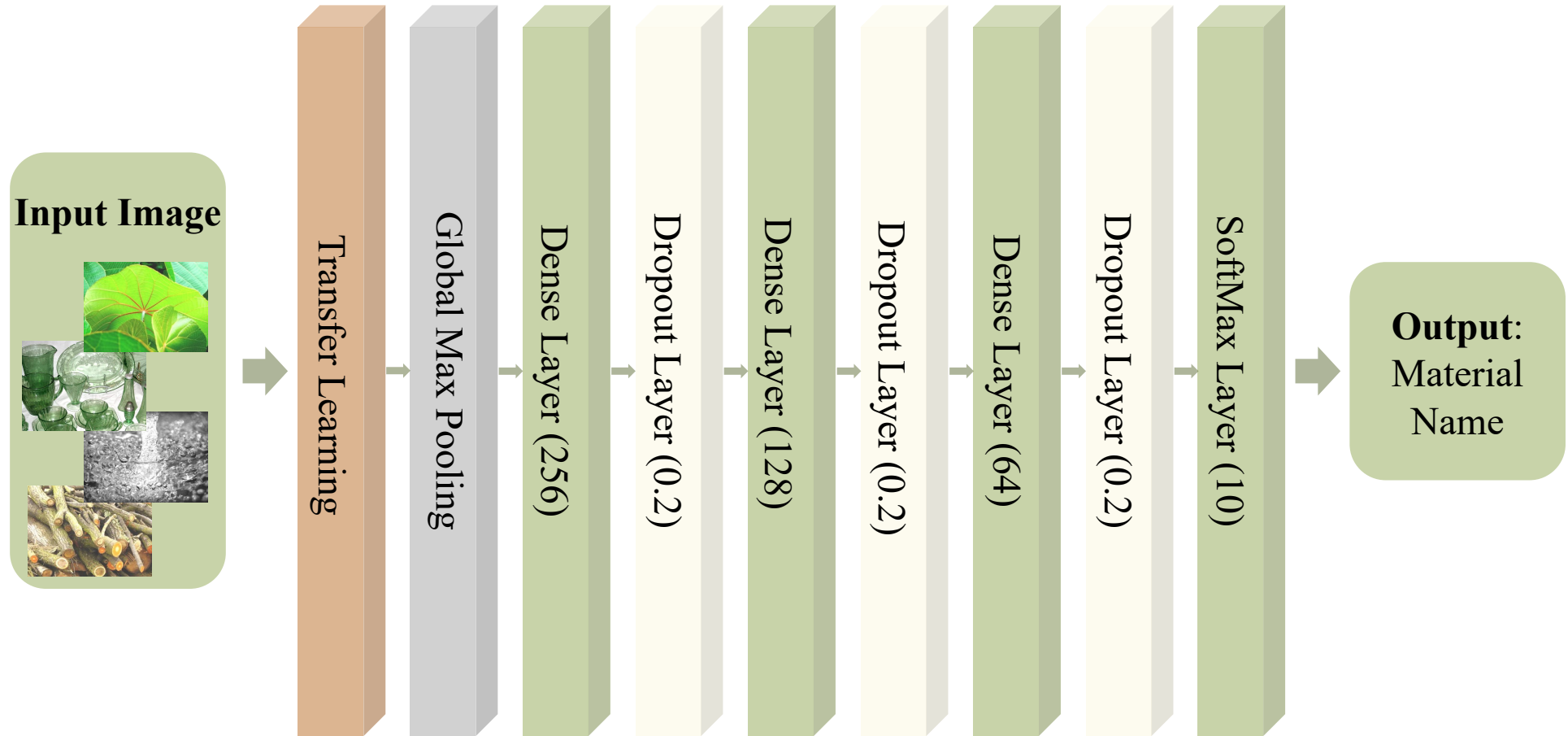
**New Image Size:** (150, 150)  
**Normalize:** from 0-255 to 0-1

**3. Resize & Normalize**

# Vanilla CNN Model



# Transfer Learning



# Models:

- Vanilla CNN
- TF - VGG16
- TF - ResNet50
- TF - Xception
- TF - MobileNet
- TF - DenseNet121
- TF - DenseNet201
- TF - EfficientNetV2B0
- TF - InceptionV3

\* *TF: transfer learning*

## Step 1

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Train all the Models on the Training Dataset and Record Validation Accuracy

## Step 2

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Use Best Architecture to Run Further Experiments: Data Augmentation, Masks...

## Step 3

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Compare Validation Accuracies to Determine Best Performing Model

## Step 4

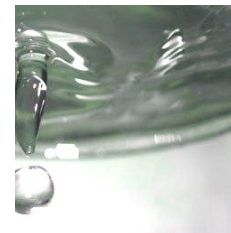
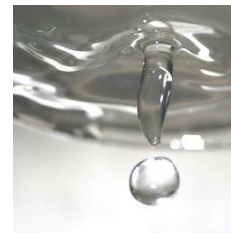
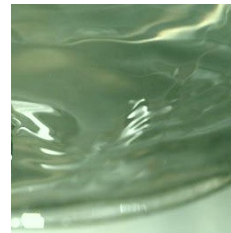
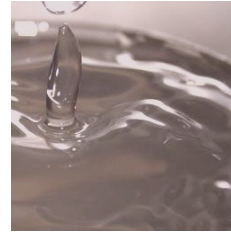
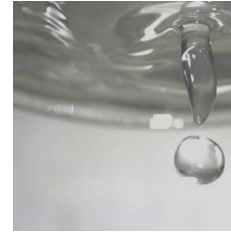
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Re-Train Best Model on Train & Validation Dataset and Record Test Accuracy



# Data Augmentation

- **Random Crop** ( $w=256, h=256$ )
- **Horizontal Flip** ( $p=0.5$ )
- **Vertical flip** ( $p = 0.5$ )
- **RGB shift** ( $p = 0.4$ )
- **Color Jitter** ( $p = 0.2$ )
- **Brightness Contrast** ( $p = 0.2$ )

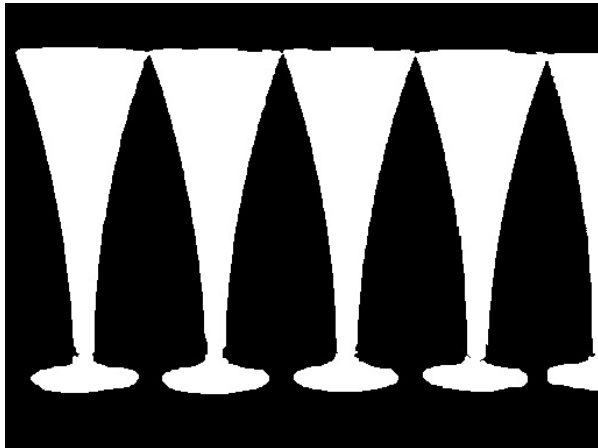


# Applying Masks to Images

**Original Image**



**Mask**



**Object of Interest**



# Hyperparameter Optimization

Model	Val Accuracy	Learning rate	Dropout rate	Size dense layers
DenseNet201	0.7940	0.0023	0.4	256/192/48
Xception	0.7549	0.00017	0.3	256/128/48

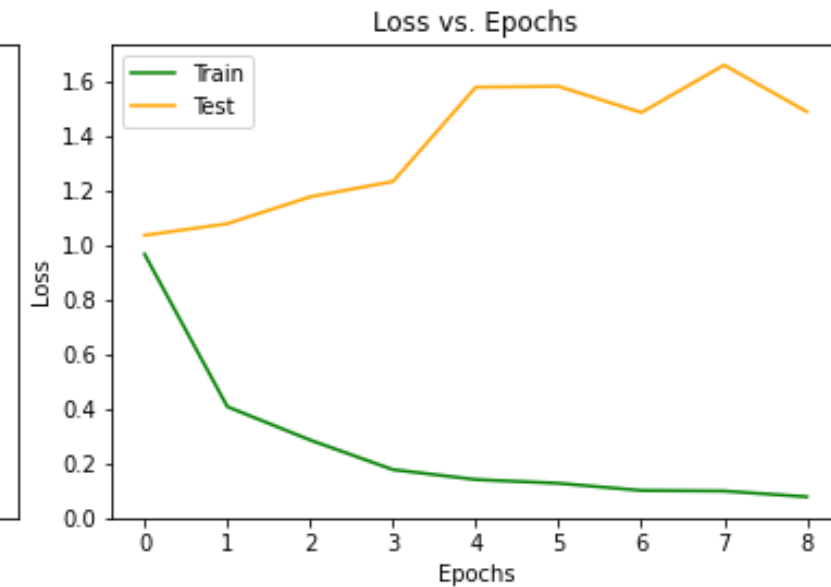
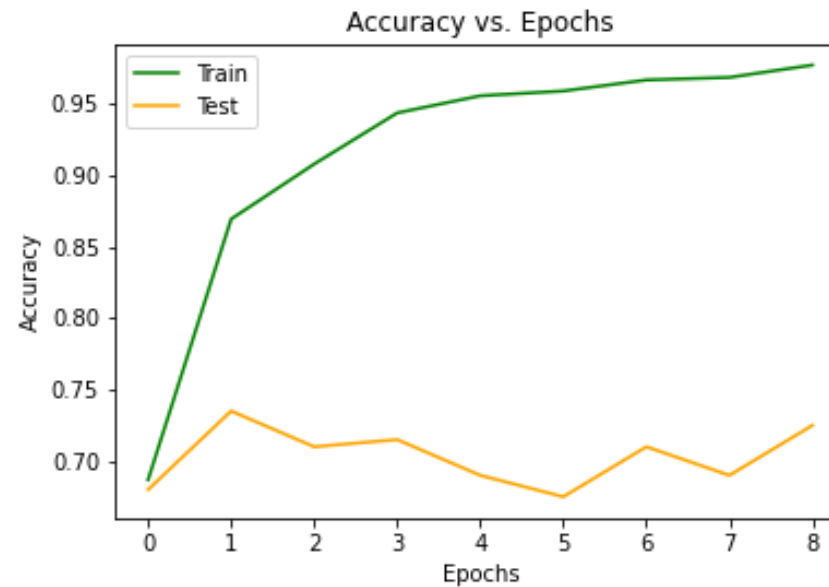


Hyper Parameter	Ranges	Step Size
Units Dense layer 1	(128 – 512)	128
Units Dense layer 2	(64 – 256)	64
Units Dense layer 3	(16 – 64)	16
Learning rate	(0.0001 – 0.01)	Log sampling
Dropout probability	(0.1 – 0.5)	0.1

# Results – Best Model

**Xception on Augmented Data: 73.5% Accuracy**

Class	Precision
Fabric	0.667
Foliage	0.857
Glass	0.714
Leather	0.824
Metal	0.654
Paper	0.8
Plastic	0.615
Stone	0.812
Water	0.783
Wood	0.714



# Garbage Classification

Classify Garbage



Flickr Garbage

Cardboard	Trash	Glass	Metal	Paper	Plastic
N/A	N/A				

Accuracy: 52% using model

Source: Garbage Dataset (Kaggle): <https://www.kaggle.com/datasets/asdasdasdasdas/garbage-classification>

# Key Takeaways

## High Accuracy

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Better performance than majority of models in literature... but lower than human performance and state-of-the-art model

**73.5% accuracy**  
**vs**  
**84% accuracy**

## Simplicity

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Main Benefit: Simpler Approach than the State-of-the-Art Model, easier to code and use

**Transfer Learning**  
**&**  
**Dense Layers**

## Generalization

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Approach is suitable for practical applications as it is easy to run and achieves decent performance on practical examples

**Garbage Accuracy:**  
**52%**

