PHARMACEUTICAL DRUGS & VITAMINS IMAGE CLASSIFICATION MODEL

PROBLEM STATEMENT

Many people **struggle** to **recall medication names** or get them mixed up, which can be **risky**. Our project addresses this by developing an image classification model for **pharmaceutical drugs & vitamin image classification** using **Convolutional Neural Network,** which identifies medication names from images. Our model aims to empower individuals to confidently recognize their medications, reduce errors, and simplify their daily lives.

DATA OVERVIEW

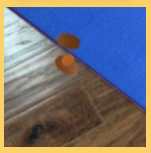
Our project utilizes a dataset of **synthetic images** on varied backgrounds. These labeled images depict various common pharmaceutical drugs and vitamins, capturing different **shapes**, **colors**, and **forms**. This diverse collection of synthetic data is crucial for training our deep learning model. By learning from these images, the model aims to accurately **classify** and identify **different medications,** ultimately helping the public distinguish their drugs more easily based on visual appearance.

EXPLORATORY DATA ANALYSIS

The dataset has **10 types of medicines**, each class consists of 1000 images. Therefore, the image distribution is **balanced**.

ALAXAN

BACTIDOL



BIOFLU

BIOGESIC

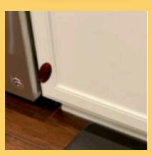
DAYZINC

DECOLGEN

FISH OIL

KREMIL S

MEDICOL



NEOZEP

BRIGHTNESS

Images are **generally bright,** shown by the RGB values often peaking at 255.

COLOR AMONG CLASSES

The most prominent difference is shown by the **blue value** in RGB.

- **Alaxan, Bactidol, Bioflu:** higher blue tones, appearing cooler.
- **Biogesic, Fish Oil, Kremil S:** relatively lower blue peaks, resulting in warmer images.
- **DayZinc, Decolgen, Medicol, Neozep:** lowest blue values, indicating the warmest tones.

PREPROCESSING

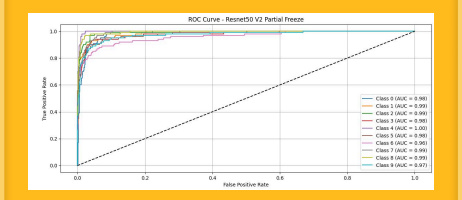
1. **Image standardization**
   Balances the brightness and contrast
2. **Flip left-right**
   Adds partial variability and reduces overfitting risks
3. **Crop**
   Introduces variation in scale
4. **Resize to 224x224x3**
   Adjusts with CNN models default input (w = h = 224px, color channels = 3)
5. **Random contrast**
   Combats over-reliance on lighting
6. **Random brightness**
   Simulates different lighting conditions in real situations

MODELS

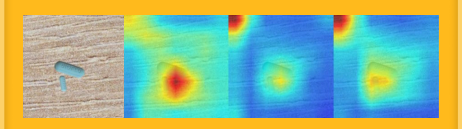
Structure: GlobalAveragePooling2D – Dense Layer (512 neurons, ReLU) – Dropout 0.3 – Dense Layer (10 neurons, softmax)
Training: 100 epochs, Adam 1e-4, EarlyStopping, Categorical Cross Entropy | **Attention Map** shown for the last 3 layers only

#1 RESNET50V2 MODIFIED MODEL

ACCURACY	F1-SCORE	PRECISION	RECALL
0.84	0.84	0.84	0.84



- **AUC Range**: 0.96 – 1.00
- **Best Performance**: Biogesic (1.00)
- **Lowest Performance**: Fish Oil (0.96)

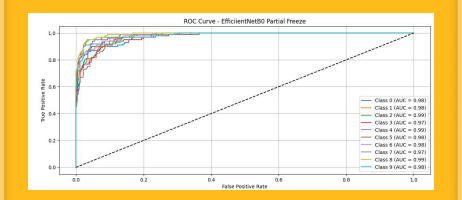


More focused on the object, though some attention remained on noisy background areas.

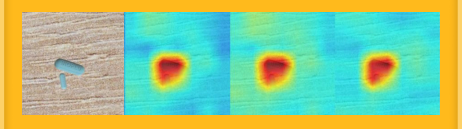
BEST MODEL

#2 EFFICIENTNETB0 MODIFIED MODEL

ACCURACY	F1-SCORE	PRECISION	RECALL
0.80	0.80	0.80	0.80



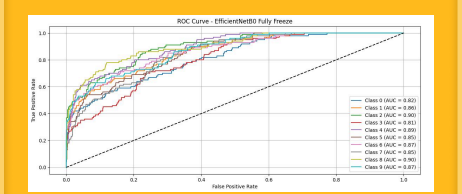
- **AUC Range**: 0.97 – 0.99
- **Best Performance**: Bactidol (0.99)
- **Lowest Performance**: Bioflu, Fish Oil (0.97)



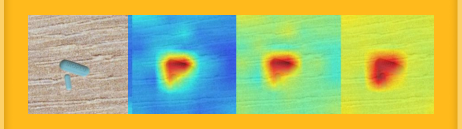
Focused on the main object and learned to do so more quickly than the fully frozen version.

#3 EFFICIENTNETB0 BASE MODEL

ACCURACY	F1-SCORE	PRECISION	RECALL
0.49	0.49	0.49	0.49



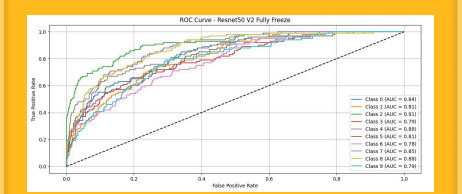
- **AUC Score Range**: 0.81 – 0.90
- **Best Performance**: Bactidol, Kremil S
- **Lowest Performance**: Bioflu (0.81)



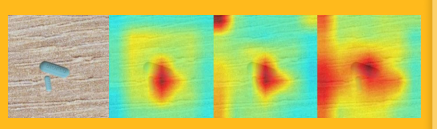
Model is capable of focusing on the main object.

#4 RESNET50V2 BASE MODEL

ACCURACY	F1-SCORE	PRECISION	RECALL
0.44	0.44	0.45	0.44



- **AUC Range**: 0.78 – 0.91
- **Best Performance**: Bactidol (0.91)
- **Lowest Performance**: Decolgen (0.78)



Generally unfocused, with attention scattered across the image rather than precisely on the main object.

CONCLUSION

- **Unfreezing several layers is highly impactful**, allowing the model to adapt with the specific data features.
- **A fully frozen backbone limits adaptation capability**, not robust enough for a multiclass classification task.
- **The partially frozen ResNet50V2 model is the most stable**, achieving the highest evaluation metrics.
- Some **challenges** are present:

VISUAL SIMILARITY **NOISY REAL DATA** **LIMITED DATA SCOPE**

FUTURE OPPORTUNITIES

- **Improve Accuracy with Multimodal Input**: Combine with metadata like manufacturer names to differentiate visually similar drugs.
- **Enhance User Verification**: Display detailed drug information (usage, dosage, etc.) with predictions, allowing users to confirm the result meets their needs.
- **Integrate Commercial Partnerships**: Collaborate with pharmacies to show users where to find medications, creating a business model through subscription fees.
- **Expand the Dataset**: Gradually add more diverse medications to make the model more comprehensive and robust.

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