

Using minimum support = 0.01 and minimum confidence threshold = 0.1, what are the association rules you can extract from your dataset? (0.5 point)

```
In [6]: import pandas as pd
from mlxtend.preprocessing import TransactionEncoder
from mlxtend.frequent_patterns import fpgrowth
from mlxtend.frequent_patterns import association_rules

dataset_url = '/Users/sarahsamhithachella/Downloads/Grocery_Items_10.csv'

df = pd.read_csv('/Users/sarahsamhithachella/Downloads/Grocery_Items_10.csv')

transactions = df.apply(lambda row: row.dropna().tolist(), axis=1).tolist()
te = TransactionEncoder()
te_ary = te.fit(transactions).transform(transactions)

df_transformed = pd.DataFrame(te_ary, columns=te.columns_)

frequent_itemsets = fpgrowth(df_transformed, min_support=0.01, use_colnames=True)
rules = association_rules(frequent_itemsets, metric="confidence", min_threshold=0.1)

print("Frequent Itemsets:")
print(frequent_itemsets)

print("\nAssociation Rules:")
rules.to_csv('association_rules.csv', index=False)
display(rules)
```

Frequent Itemsets:

	support	itemsets
0	0.018750	(sugar)
1	0.015625	(beverages)
2	0.058375	(bottled water)
3	0.037875	(butter)
4	0.027125	(chicken)
...	...	...
62	0.014375	(whole milk, rolls/buns)
63	0.010750	(other vegetables, rolls/buns)
64	0.016000	(other vegetables, whole milk)
65	0.012125	(whole milk, yogurt)
66	0.012125	(soda, whole milk)

[67 rows x 2 columns]

Association Rules:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction	zhangs_metric
0	(rolls/buns)	(whole milk)	0.111625	0.15750	0.014375	0.128779	0.817647	-0.003206	0.967034	-0.200668
1	(other vegetables)	(whole milk)	0.119750	0.15750	0.016000	0.133612	0.848328	-0.002861	0.972428	-0.168822
2	(whole milk)	(other vegetables)	0.157500	0.11975	0.016000	0.101587	0.848328	-0.002861	0.979784	-0.175062
3	(yogurt)	(whole milk)	0.088750	0.15750	0.012125	0.136620	0.867427	-0.001853	0.975816	-0.143630
4	(soda)	(whole milk)	0.098625	0.15750	0.012125	0.122940	0.780574	-0.003408	0.960596	-0.237727

Use minimum support values (msv): 0.001, 0.005, 0.01, 0.05 and minimum confidence threshold (mct): 0.05, 0.075, 0.1. For each pair (msv, mct), find the number of association rules extracted from the dataset. Construct a heatmap using Seaborn data visualization library to show the count results such that the x- axis is msv and the y-axis is mct. (2.5 points)

```
In [18]: import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from mlxtend.preprocessing import TransactionEncoder
from mlxtend.frequent_patterns import fpgrowth, association_rules

df = pd.read_csv('/Users/sarahsamhithachella/Downloads/Grocery_Items_10.csv')

transactions = df.apply(lambda row: row.dropna().tolist(), axis=1).tolist()
te = TransactionEncoder()
te_ary = te.fit(transactions).transform(transactions)

df_transformed = pd.DataFrame(te_ary, columns=te.columns_)

msv_values = [0.001, 0.005, 0.01, 0.05]
mct_values = [0.05, 0.075, 0.1]

rules_counts = pd.DataFrame(index=msv_values, columns=mct_values)

for msv in msv_values:
    for mct in mct_values:
        frequent_itemsets = fpgrowth(df_transformed, min_support=msv, use_colnames=True)

        rules = association_rules(frequent_itemsets, metric="confidence", min_threshold=mct)

        rules_counts.at[msv, mct] = len(rules)

        print(f"Number of rules for (msv={msv}, mct={mct}): {len(rules)}")

rules_counts = rules_counts.apply(pd.to_numeric)
```

```
plt.figure(figsize=(10, 6))
sns.heatmap(rules_counts, annot=True, cmap="Blues", fmt="g", linewidths=.5)
plt.title("Number of Association Rules")
plt.xlabel("Minimum Confidence Threshold (mct)")
plt.ylabel("Minimum Support Value (msv)")
plt.show()
```

```
Number of rules for (msv=0.001, mct=0.05): 534
Number of rules for (msv=0.001, mct=0.075): 307
Number of rules for (msv=0.001, mct=0.1): 162
Number of rules for (msv=0.005, mct=0.05): 61
Number of rules for (msv=0.005, mct=0.075): 42
Number of rules for (msv=0.005, mct=0.1): 23
Number of rules for (msv=0.01, mct=0.05): 10
Number of rules for (msv=0.01, mct=0.075): 10
Number of rules for (msv=0.01, mct=0.1): 5
Number of rules for (msv=0.05, mct=0.05): 0
Number of rules for (msv=0.05, mct=0.075): 0
Number of rules for (msv=0.05, mct=0.1): 0
```



List the association rule(s) (i.e., one or more rules depending on your dataset) that have the highest confidence for minimum support = 0.005. What is that confidence value? (1 point)

```
In [8]: import pandas as pd
from mlxtend.preprocessing import TransactionEncoder
from mlxtend.frequent_patterns import fpgrowth, association_rules

df = pd.read_csv('/Users/sarahsamhithachella/Downloads/Grocery_Items_10.csv')

transactions = df.apply(lambda row: row.dropna().tolist(), axis=1).tolist()
te = TransactionEncoder()
te_ary = te.fit(transactions).transform(transactions)
```

```

df_transformed = pd.DataFrame(te_ary, columns=te.columns_)

min_support = 0.005

frequent_itemsets = fpgrowth(df_transformed, min_support=min_support, use_colnames=True)

rules = association_rules(frequent_itemsets, metric="confidence", min_threshold=0.0)

max_confidence_rule = rules.loc[rules['confidence'].idxmax()]

print("Association Rule(s) with the Highest Confidence:")
print(max_confidence_rule)

```

```

Association Rule(s) with the Highest Confidence:
antecedents          (bottled beer)
consequents          (whole milk)
antecedent support    0.042125
consequent support    0.1575
support              0.008125
confidence            0.192878
lift                 1.224624
leverage             0.00149
conviction            1.043833
zhangs_metric        0.19149
Name: 49, dtype: object

```

## High Confidence Value

The confidence value is 0.192878. A confidence level of 0.192878 indicates that "whole milk" is purchased in almost 19.29% of the cases in which "bottled beer" is present.

In [68]: `pip install tensorflow`

```
Collecting tensorflow
  Obtaining dependency information for tensorflow from https://files.pythonhosted.org/packages/85/15/cf99a373812d37f8ae99752a34a9f5f690d820ceb5b302e922705bc18944/tensorflow-2.15.0-cp311-cp311-macosx_12_0_arm64.whl.metadata
  Downloading tensorflow-2.15.0-cp311-cp311-macosx_12_0_arm64.whl.metadata (3.6 kB)
Collecting tensorflow-macos==2.15.0 (from tensorflow)
  Obtaining dependency information for tensorflow-macos==2.15.0 from https://files.pythonhosted.org/packages/eb/9f/0759e2fea4a3c48f070b64811c2c57036b46353ba87263afc810b8f4188a/tensorflow_macos-2.15.0-cp311-cp311-macosx_12_0_arm64.whl.metadata
  Downloading tensorflow_macos-2.15.0-cp311-cp311-macosx_12_0_arm64.whl.metadata (4.2 kB)
Collecting absl-py>=1.0.0 (from tensorflow-macos==2.15.0->tensorflow)
  Obtaining dependency information for absl-py>=1.0.0 from https://files.pythonhosted.org/packages/01/e4/dc0a1dcc4e74e08d7abeda b278c795eef54a224363bb18f5692f416d834f/absl_py-2.0.0-py3-none-any.whl.metadata
  Downloading absl_py-2.0.0-py3-none-any.whl.metadata (2.3 kB)
Collecting astunparse>=1.6.0 (from tensorflow-macos==2.15.0->tensorflow)
  Downloading astunparse-1.6.3-py2.py3-none-any.whl (12 kB)
Collecting flatbuffers>=23.5.26 (from tensorflow-macos==2.15.0->tensorflow)
  Obtaining dependency information for flatbuffers>=23.5.26 from https://files.pythonhosted.org/packages/6f/12/d5c79ee252793ffe845d58a913197bfa02ae9a0b5c9bc3dc4b58d477b9e7/flatbuffers-23.5.26-py2.py3-none-any.whl.metadata
  Downloading flatbuffers-23.5.26-py2.py3-none-any.whl.metadata (850 bytes)
Collecting gast!=0.5.0,!=0.5.1,!=0.5.2,>=0.2.1 (from tensorflow-macos==2.15.0->tensorflow)
  Downloading gast-0.5.4-py3-none-any.whl (19 kB)
Collecting google-pasta>=0.1.1 (from tensorflow-macos==2.15.0->tensorflow)
  Downloading google_pasta-0.2.0-py3-none-any.whl (57 kB)


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57.5/57.5 kB 2.5 MB/s eta 0:00:00
Requirement already satisfied: h5py>=2.9.0 in /Users/sarahsamhithachella/anaconda3/lib/python3.11/site-packages (from tensorflow-macos==2.15.0->tensorflow) (3.7.0)
Collecting libclang>=13.0.0 (from tensorflow-macos==2.15.0->tensorflow)
  Obtaining dependency information for libclang>=13.0.0 from https://files.pythonhosted.org/packages/32/1f/981809b77b71972beec34b3ff5422c1b1f7e519daac7b3cbd055c05ba2cf/libclang-16.0.6-py2.py3-none-macosx_11_0_arm64.whl.metadata
  Downloading libclang-16.0.6-py2.py3-none-macosx_11_0_arm64.whl.metadata (5.2 kB)
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  Downloading ml_dtypes-0.2.0-cp311-cp311-macosx_10_9_universal2.whl.metadata (20 kB)
Requirement already satisfied: numpy<2.0.0,>=1.23.5 in /Users/sarahsamhithachella/anaconda3/lib/python3.11/site-packages (from tensorflow-macos==2.15.0->tensorflow) (1.24.3)
Collecting opt-einsum>=2.3.2 (from tensorflow-macos==2.15.0->tensorflow)
  Downloading opt_einsum-3.3.0-py3-none-any.whl (65 kB)


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Requirement already satisfied: packaging in /Users/sarahsamhithachella/anaconda3/lib/python3.11/site-packages (from tensorflow-macos==2.15.0->tensorflow) (23.0)
Collecting protobuf!=4.21.0,!=4.21.1,!=4.21.2,!=4.21.3,!=4.21.4,!=4.21.5,<5.0.0dev,>=3.20.3 (from tensorflow-macos==2.15.0->tensorflow)
  Obtaining dependency information for protobuf!=4.21.0,!=4.21.1,!=4.21.2,!=4.21.3,!=4.21.4,!=4.21.5,<5.0.0dev,>=3.20.3 from https://files.pythonhosted.org/packages/e6/db/7b2edc72807d45d72f9db42f3eb86ddaf37f9e55d923159b1dbfc9d835bc/protobuf-4.25.1-cp37-abi3-macosx_10_9_universal2.whl.metadata
  Downloading protobuf-4.25.1-cp37-abi3-macosx_10_9_universal2.whl.metadata (541 bytes)
Requirement already satisfied: setuptools in /Users/sarahsamhithachella/anaconda3/lib/python3.11/site-packages (from tensorflow-macos==2.15.0->tensorflow) (68.0.0)
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Requirement already satisfied: six>=1.12.0 in /Users/sarahsamhithachella/anaconda3/lib/python3.11/site-packages (from tensorflow-macos==2.15.0->tensorflow) (1.16.0)  
Collecting termcolor>=1.1.0 (from tensorflow-macos==2.15.0->tensorflow)  
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Requirement already satisfied: typing-extensions>=3.6.6 in /Users/sarahsamhithachella/anaconda3/lib/python3.11/site-packages (from tensorflow-macos==2.15.0->tensorflow) (4.7.1)  
Requirement already satisfied: wrapt<1.15,>=1.11.0 in /Users/sarahsamhithachella/anaconda3/lib/python3.11/site-packages (from tensorflow-macos==2.15.0->tensorflow) (1.14.1)  
Collecting tensorflow-io-gcs-filesystem>=0.23.1 (from tensorflow-macos==2.15.0->tensorflow)  
 Obtaining dependency information for tensorflow-io-gcs-filesystem>=0.23.1 from [https://files.pythonhosted.org/packages/5b/e9/1444afc87596a90066704cc46ed661a4e7b348eec03a3fc2ca10ab917254/tensorflow\\_io\\_gcs\\_filesystem-0.34.0-cp311-cp311-macosx\\_12\\_0\\_arm64.whl.metadata](https://files.pythonhosted.org/packages/5b/e9/1444afc87596a90066704cc46ed661a4e7b348eec03a3fc2ca10ab917254/tensorflow_io_gcs_filesystem-0.34.0-cp311-cp311-macosx_12_0_arm64.whl.metadata)  
 Downloading tensorflow\_io\_gcs\_filesystem-0.34.0-cp311-cp311-macosx\_12\_0\_arm64.whl.metadata (14 kB)  
Collecting grpcio<2.0,>=1.24.3 (from tensorflow-macos==2.15.0->tensorflow)  
 Obtaining dependency information for grpcio<2.0,>=1.24.3 from [https://files.pythonhosted.org/packages/92/93/3cbc00a269b46277ff26355074a8315eeb4c87240c27d6f7efeabe818fd9/grpcio-1.59.3-cp311-cp311-macosx\\_10\\_10\\_universal2.whl.metadata](https://files.pythonhosted.org/packages/92/93/3cbc00a269b46277ff26355074a8315eeb4c87240c27d6f7efeabe818fd9/grpcio-1.59.3-cp311-cp311-macosx_10_10_universal2.whl.metadata)  
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Collecting tensorboard<2.16,>=2.15 (from tensorflow-macos==2.15.0->tensorflow)  
 Obtaining dependency information for tensorboard<2.16,>=2.15 from <https://files.pythonhosted.org/packages/6e/0c/1059a6682cf2cc1fcc0d5327837b5672fe4f5574255fa5430d0a8ceb75e9/tensorboard-2.15.1-py3-none-any.whl.metadata>  
 Downloading tensorboard-2.15.1-py3-none-any.whl.metadata (1.7 kB)  
Collecting tensorflow-estimator<2.16,>=2.15.0 (from tensorflow-macos==2.15.0->tensorflow)  
 Obtaining dependency information for tensorflow-estimator<2.16,>=2.15.0 from [https://files.pythonhosted.org/packages/b6/c8/2f823c8958d5342eafc6dd3e922f0cc4fcf8c2e0460284cc462dae3b60a0/tensorflow\\_estimator-2.15.0-py2.py3-none-any.whl.metadata](https://files.pythonhosted.org/packages/b6/c8/2f823c8958d5342eafc6dd3e922f0cc4fcf8c2e0460284cc462dae3b60a0/tensorflow_estimator-2.15.0-py2.py3-none-any.whl.metadata)  
 Downloading tensorflow\_estimator-2.15.0-py2.py3-none-any.whl.metadata (1.3 kB)  
Collecting keras<2.16,>=2.15.0 (from tensorflow-macos==2.15.0->tensorflow)  
 Obtaining dependency information for keras<2.16,>=2.15.0 from <https://files.pythonhosted.org/packages/fc/a7/0d4490de967a67f68a538cc9cdb259bff971c4b5787f7765dc7c8f118f71/keras-2.15.0-py3-none-any.whl.metadata>  
 Downloading keras-2.15.0-py3-none-any.whl.metadata (2.4 kB)  
Requirement already satisfied: wheel<1.0,>=0.23.0 in /Users/sarahsamhithachella/anaconda3/lib/python3.11/site-packages (from astunparse>=1.6.0->tensorflow-macos==2.15.0->tensorflow) (0.38.4)  
Collecting google-auth<3,>=1.6.3 (from tensorboard<2.16,>=2.15->tensorflow-macos==2.15.0->tensorflow)  
 Obtaining dependency information for google-auth<3,>=1.6.3 from [https://files.pythonhosted.org/packages/86/a7/75911c13a242735d5aeaca6a272da380335ff4ba5f26d6b2ae20ff682d13/google\\_auth-2.23.4-py2.py3-none-any.whl.metadata](https://files.pythonhosted.org/packages/86/a7/75911c13a242735d5aeaca6a272da380335ff4ba5f26d6b2ae20ff682d13/google_auth-2.23.4-py2.py3-none-any.whl.metadata)  
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Collecting google-auth-oauthlib<2,>=0.5 (from tensorboard<2.16,>=2.15->tensorflow-macos==2.15.0->tensorflow)  
 Obtaining dependency information for google-auth-oauthlib<2,>=0.5 from [https://files.pythonhosted.org/packages/ce/33/a907b4b67245647746dde8d61e1643ef5d210c88e090d491efd89eff9f95/google\\_auth\\_oauthlib-1.1.0-py2.py3-none-any.whl.metadata](https://files.pythonhosted.org/packages/ce/33/a907b4b67245647746dde8d61e1643ef5d210c88e090d491efd89eff9f95/google_auth_oauthlib-1.1.0-py2.py3-none-any.whl.metadata)  
 Downloading google\_auth\_oauthlib-1.1.0-py2.py3-none-any.whl.metadata (2.7 kB)  
Requirement already satisfied: markdown>=2.6.8 in /Users/sarahsamhithachella/anaconda3/lib/python3.11/site-packages (from tensorboard<2.16,>=2.15->tensorflow-macos==2.15.0->tensorflow) (3.4.1)  
Collecting protobuf!=4.21.0,!4.21.1,!4.21.2,!4.21.3,!4.21.4,!4.21.5,<5.0.0dev,>=3.20.3 (from tensorflow-macos==2.15.0->tensorflow)  
 Obtaining dependency information for protobuf!=4.21.0,!4.21.1,!4.21.2,!4.21.3,!4.21.4,!4.21.5,<5.0.0dev,>=3.20.3 from [https://files.pythonhosted.org/packages/cb/d3/a164038605494d49acc4f9cda1c0bc200b96382c53edd561387263bb181d/protobuf-4.23.4-cp37-abi3-macosx\\_10\\_9\\_universal2.whl.metadata](https://files.pythonhosted.org/packages/cb/d3/a164038605494d49acc4f9cda1c0bc200b96382c53edd561387263bb181d/protobuf-4.23.4-cp37-abi3-macosx_10_9_universal2.whl.metadata)  
 Downloading protobuf-4.23.4-cp37-abi3-macosx\_10\_9\_universal2.whl.metadata (540 bytes)  
Requirement already satisfied: requests<3,>=2.21.0 in /Users/sarahsamhithachella/anaconda3/lib/python3.11/site-packages (from tensorflow-macos==2.15.0->tensorflow) (2.31.0)

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ensorboard<2.16,>=2.15->tensorflow-macos==2.15.0->tensorflow) (2.31.0)
Collecting tensorboard-data-server<0.8.0,>=0.7.0 (from tensorboard<2.16,>=2.15->tensorflow-macos==2.15.0->tensorflow)
  Obtaining dependency information for tensorboard-data-server<0.8.0,>=0.7.0 from https://files.pythonhosted.org/packages/7a/13/e503968fefabd4c6b2650af21e110aa8466fe21432cd7c43a84577a89438/tensorboard_data_server-0.7.2-py3-none-any.whl.metadata
  Downloading tensorboard_data_server-0.7.2-py3-none-any.whl.metadata (1.1 kB)
Requirement already satisfied: werkzeug>=1.0.1 in /Users/sarahsamhithachella/anaconda3/lib/python3.11/site-packages (from tensorboard<2.16,>=2.15->tensorflow-macos==2.15.0->tensorflow) (2.2.3)
Collecting cachetools<6.0,>=2.0.0 (from google-auth<3,>=1.6.3->tensorboard<2.16,>=2.15->tensorflow-macos==2.15.0->tensorflow)
  Obtaining dependency information for cachetools<6.0,>=2.0.0 from https://files.pythonhosted.org/packages/a2/91/2d843adb9fbd911e0da45fbf6f18ca89d07a087c3daa23e955584f90ebf4/cachetools-5.3.2-py3-none-any.whl.metadata
  Downloading cachetools-5.3.2-py3-none-any.whl.metadata (5.2 kB)
Requirement already satisfied: pyasn1-modules>=0.2.1 in /Users/sarahsamhithachella/anaconda3/lib/python3.11/site-packages (from google-auth<3,>=1.6.3->tensorboard<2.16,>=2.15->tensorflow-macos==2.15.0->tensorflow) (0.2.8)
Collecting rsa<5,>=3.1.4 (from google-auth<3,>=1.6.3->tensorboard<2.16,>=2.15->tensorflow-macos==2.15.0->tensorflow)
  Downloading rsa-4.9-py3-none-any.whl (34 kB)
Collecting requests-oauthlib>=0.7.0 (from google-auth-oauthlib<2,>=0.5->tensorboard<2.16,>=2.15->tensorflow-macos==2.15.0->tensorflow)
  Downloading requests_oauthlib-1.3.1-py2.py3-none-any.whl (23 kB)
Requirement already satisfied: charset-normalizer<4,>=2 in /Users/sarahsamhithachella/anaconda3/lib/python3.11/site-packages (from requests<3,>=2.21.0->tensorboard<2.16,>=2.15->tensorflow-macos==2.15.0->tensorflow) (2.0.4)
Requirement already satisfied: idna<4,>=2.5 in /Users/sarahsamhithachella/anaconda3/lib/python3.11/site-packages (from requests<3,>=2.21.0->tensorboard<2.16,>=2.15->tensorflow-macos==2.15.0->tensorflow) (3.4)
Requirement already satisfied: urllib3<3,>=1.21.1 in /Users/sarahsamhithachella/anaconda3/lib/python3.11/site-packages (from requests<3,>=2.21.0->tensorboard<2.16,>=2.15->tensorflow-macos==2.15.0->tensorflow) (1.26.16)
Requirement already satisfied: certifi>=2017.4.17 in /Users/sarahsamhithachella/anaconda3/lib/python3.11/site-packages (from requests<3,>=2.21.0->tensorboard<2.16,>=2.15->tensorflow-macos==2.15.0->tensorflow) (2023.7.22)
Requirement already satisfied: MarkupSafe>=2.1.1 in /Users/sarahsamhithachella/anaconda3/lib/python3.11/site-packages (from werkzeug>=1.0.1->tensorboard<2.16,>=2.15->tensorflow-macos==2.15.0->tensorflow) (2.1.1)
Requirement already satisfied: pyasn1<0.5.0,>=0.4.6 in /Users/sarahsamhithachella/anaconda3/lib/python3.11/site-packages (from pyasn1-modules>=0.2.1->google-auth<3,>=1.6.3->tensorboard<2.16,>=2.15->tensorflow-macos==2.15.0->tensorflow) (0.4.8)
Collecting oauthlib>=3.0.0 (from requests-oauthlib>=0.7.0->google-auth-oauthlib<2,>=0.5->tensorboard<2.16,>=2.15->tensorflow-macos==2.15.0->tensorflow)
  Downloading oauthlib-3.2.2-py3-none-any.whl (151 kB)
  _____ 151.7/151.7 kB 10.4 MB/s eta 0:00:00
Downloading tensorflow-2.15.0-cp311-cp311-macosx_12_0_arm64.whl (2.1 kB)
Downloading tensorflow_macos-2.15.0-cp311-cp311-macosx_12_0_arm64.whl (208.8 MB)
  _____ 208.8/208.8 MB 2.9 MB/s eta 0:00:0000:0100:02
Downloading absl_py-2.0.0-py3-none-any.whl (130 kB)
  _____ 130.2/130.2 kB 3.6 MB/s eta 0:00:00
Downloading flatbuffers-23.5.26-py2.py3-none-any.whl (26 kB)
Downloading grpcio-1.59.3-cp311-cp311-macosx_10_10_universal2.whl (9.6 MB)
  _____ 9.6/9.6 MB 3.3 MB/s eta 0:00:0000:0100:01
Downloading keras-2.15.0-py3-none-any.whl (1.7 MB)
  _____ 1.7/1.7 MB 5.0 MB/s eta 0:00:0000:0100:01
Downloading libclang-16.0.6-py2.py3-none-macosx_11_0_arm64.whl (20.6 MB)
  _____ 20.6/20.6 MB 3.7 MB/s eta 0:00:0000:0100:01
Downloading ml_dtypes-0.2.0-cp311-cp311-macosx_10_9_universal2.whl (1.2 MB)
  _____ 1.2/1.2 MB 4.6 MB/s eta 0:00:0000:0100:01
```



```

Downloading tensorboard-2.15.1-py3-none-any.whl (5.5 MB)
 5.5/5.5 MB 5.1 MB/s eta 0:00:000:0100:01
Downloading protobuf-4.23.4-cp37-abi3-macosx_10_9_universal2.whl (400 kB)
 400.3/400.3 kB 5.8 MB/s eta 0:00:00a 0:00:01
Downloading tensorflow_estimator-2.15.0-py2.py3-none-any.whl (441 kB)
 442.0/442.0 kB 5.9 MB/s eta 0:00:00a 0:00:01
Downloading tensorflow_io_gcs_filesystem-0.34.0-cp311-cp311-macosx_12_0_arm64.whl (1.9 MB)
 1.9/1.9 MB 4.3 MB/s eta 0:00:000:0100:01
Downloading google_auth-2.23.4-py2.py3-none-any.whl (183 kB)
 183.3/183.3 kB 2.9 MB/s eta 0:00:00a 0:00:01
Downloading google_auth_oauthlib-1.1.0-py2.py3-none-any.whl (19 kB)
Downloading tensorboard_data_server-0.7.2-py3-none-any.whl (2.4 kB)
Downloading cachetools-5.3.2-py3-none-any.whl (9.3 kB)
Installing collected packages: libclang, flatbuffers, termcolor, tensorflow-io-gcs-filesystem, tensorflow-estimator, tensorboar
d-data-server, rsa, protobuf, opt-einsum, oauthlib, ml-dtypes, keras, grpcio, google-pasta, gast, cachetools, astunparse, absl-
py, requests-oauthlib, google-auth, google-auth-oauthlib, tensorboard, tensorflow-macos, tensorflow
Successfully installed absl-py-2.0.0 astunparse-1.6.3 cachetools-5.3.2 flatbuffers-23.5.26 gast-0.5.4 google-auth-2.23.4 google
-auth-oauthlib-1.1.0 google-pasta-0.2.0 grpcio-1.59.3 keras-2.15.0 libclang-16.0.6 ml-dtypes-0.2.0 oauthlib-3.2.2 opt-einsum-3.
3.0 protobuf-4.23.4 requests-oauthlib-1.3.1 rsa-4.9 tensorboard-2.15.1 tensorboard-data-server-0.7.2 tensorflow-2.15.0 tensorfl
ow-estimator-2.15.0 tensorflow-io-gcs-filesystem-0.34.0 tensorflow-macos-2.15.0 termcolor-2.3.0
Note: you may need to restart the kernel to use updated packages.

```

[Image Classification using CNN] Construct a 4-class classification model using a convolutional neural network with the following simple architecture (2 point)]

i 1 Convolutional Layer with  $8 \times 3 \times 3$  filters.

ii 1 max pooling with  $2 \times 2$  pool size

iii Flatten the Tensor

iv 1 hidden layer with 16 nodes for fully connected neural network

v Output layer has 4 nodes (since 4 classes) using 'softmax' activation function.

(Use 'Relu' for all layers except the output layer.) for 20 epochs using 'adam' optimizer and 'categorical cross entropy' loss function. If your machine is too slow, you can reduce to 5 epochs. You can perform more epochs ( $> 20$ ) if you want to. For validation split, you will use 20%. For batch size, you can pick a size that will not slow down the training process on your machine.

Plot a graph to show the learning curves (i.e., x-axis: number of epochs; y-axis: training and validation accuracy - 2 curves) (1 points)

```
In [9]: import tensorflow as tf
from tensorflow.keras import layers, models
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.optimizers.legacy import Adam as LegacyAdam # Import the legacy optimizer
from tensorflow.keras.losses import CategoricalCrossentropy
from tensorflow.keras.preprocessing.image import ImageDataGenerator

model = models.Sequential()

# Convolutional Layer with 8 3 × 3 filters
model.add(layers.Conv2D(8, (3, 3), activation='relu', input_shape=(100, 100, 3)))

# MaxPooling Layer with 2 × 2 pool size
model.add(layers.MaxPooling2D((2, 2)))

# Flatten the Tensor
model.add(layers.Flatten())

# Hidden layer with 16 nodes for a fully connected neural network
model.add(layers.Dense(16, activation='relu'))

# Output layer has 4 nodes (since 4 classes) using 'softmax' activation function
model.add(layers.Dense(4, activation='softmax'))

model.compile(optimizer=LegacyAdam(), loss=CategoricalCrossentropy(), metrics=['accuracy'])
model.summary()

datagen = ImageDataGenerator(rescale=1./255, validation_split=0.2)

dataset_path = '/Users/sarahsamhithachella/Downloads/SarahNew/Images'

train_generator = datagen.flow_from_directory(
    dataset_path,
    target_size=(100, 100),
    batch_size=32,
    class_mode='categorical',
    subset='training'
)

validation_generator = datagen.flow_from_directory(
    dataset_path,
    target_size=(100, 100),
    batch_size=32,
    class_mode='categorical',
```

```
        subset='validation'
    )

    history = model.fit(
        train_generator,
        epochs=20,
        validation_data=validation_generator
    )

    import matplotlib.pyplot as plt

    plt.plot(history.history['accuracy'], label='Training Accuracy')
    plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
    plt.xlabel('Epochs')
    plt.ylabel('Accuracy')
    plt.legend()
    plt.show()
```

Model: "sequential\_5"

Layer (type)	Output Shape	Param #
conv2d_5 (Conv2D)	(None, 98, 98, 8)	224
max_pooling2d_5 (MaxPoolin g2D)	(None, 49, 49, 8)	0
flatten_5 (Flatten)	(None, 19208)	0
dense_10 (Dense)	(None, 16)	307344
dense_11 (Dense)	(None, 4)	68

=====  
Total params: 307636 (1.17 MB)  
Trainable params: 307636 (1.17 MB)  
Non-trainable params: 0 (0.00 Byte)

=====  
Found 558 images belonging to 4 classes.  
Found 138 images belonging to 4 classes.

Epoch 1/20

18/18 [=====] - 1s 26ms/step - loss: 1.4396 - accuracy: 0.3065 - val\_loss: 1.2241 - val\_accuracy: 0.4565

Epoch 2/20

18/18 [=====] - 0s 16ms/step - loss: 1.2190 - accuracy: 0.4194 - val\_loss: 1.1595 - val\_accuracy: 0.5217

Epoch 3/20

18/18 [=====] - 0s 17ms/step - loss: 1.1541 - accuracy: 0.5036 - val\_loss: 1.1416 - val\_accuracy: 0.5072

Epoch 4/20

18/18 [=====] - 0s 17ms/step - loss: 1.0974 - accuracy: 0.5412 - val\_loss: 1.1257 - val\_accuracy: 0.5507

Epoch 5/20

18/18 [=====] - 0s 16ms/step - loss: 1.0423 - accuracy: 0.5860 - val\_loss: 1.1333 - val\_accuracy: 0.5072

Epoch 6/20

18/18 [=====] - 0s 16ms/step - loss: 1.0419 - accuracy: 0.5753 - val\_loss: 1.1038 - val\_accuracy: 0.5507

Epoch 7/20

18/18 [=====] - 0s 16ms/step - loss: 0.9614 - accuracy: 0.6523 - val\_loss: 1.1156 - val\_accuracy: 0.5580

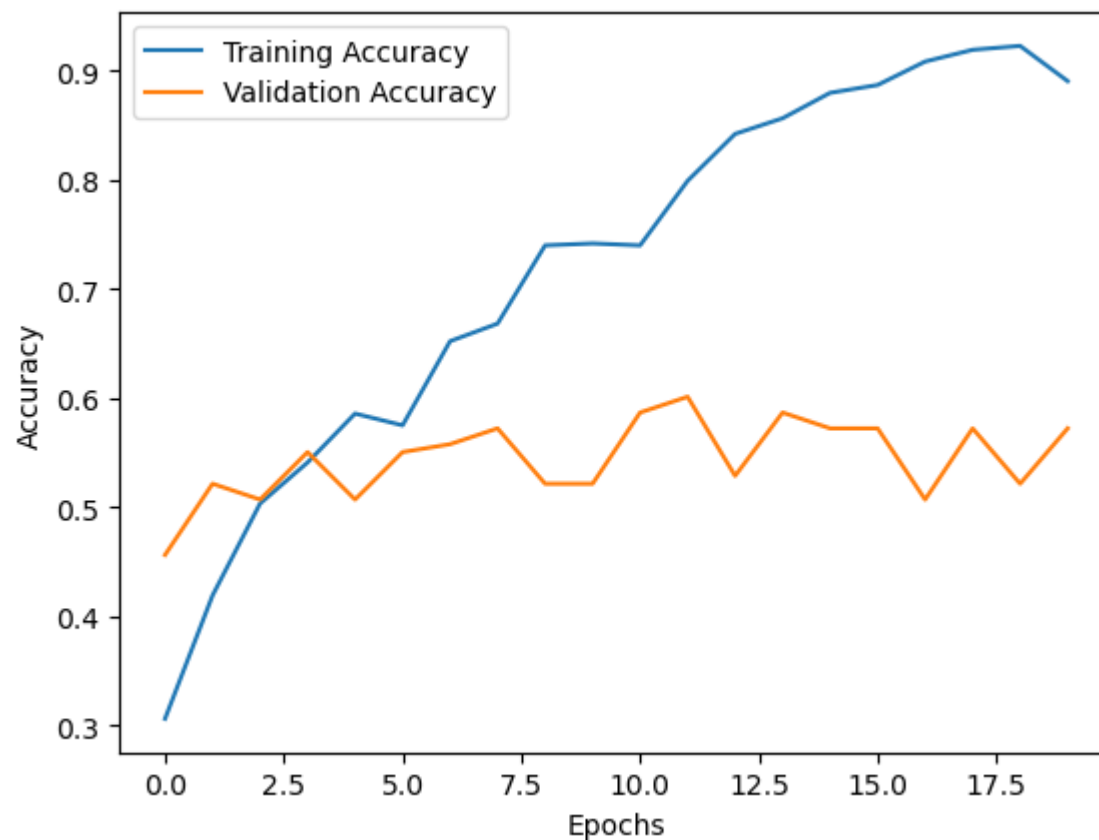
Epoch 8/20

18/18 [=====] - 0s 16ms/step - loss: 0.9240 - accuracy: 0.6685 - val\_loss: 1.0918 - val\_accuracy: 0.5725

Epoch 9/20

18/18 [=====] - 0s 16ms/step - loss: 0.8566 - accuracy: 0.7401 - val\_loss: 1.1313 - val\_accuracy: 0.52

```
17
Epoch 10/20
18/18 [=====] - 0s 16ms/step - loss: 0.8387 - accuracy: 0.7419 - val_loss: 1.1345 - val_accuracy: 0.52
17
Epoch 11/20
18/18 [=====] - 0s 16ms/step - loss: 0.8274 - accuracy: 0.7401 - val_loss: 1.0905 - val_accuracy: 0.58
70
Epoch 12/20
18/18 [=====] - 0s 16ms/step - loss: 0.7654 - accuracy: 0.7993 - val_loss: 1.0889 - val_accuracy: 0.60
14
Epoch 13/20
18/18 [=====] - 0s 18ms/step - loss: 0.6982 - accuracy: 0.8423 - val_loss: 1.1765 - val_accuracy: 0.52
90
Epoch 14/20
18/18 [=====] - 0s 16ms/step - loss: 0.6594 - accuracy: 0.8566 - val_loss: 1.1244 - val_accuracy: 0.58
70
Epoch 15/20
18/18 [=====] - 0s 16ms/step - loss: 0.6129 - accuracy: 0.8799 - val_loss: 1.1821 - val_accuracy: 0.57
25
Epoch 16/20
18/18 [=====] - 0s 16ms/step - loss: 0.5912 - accuracy: 0.8871 - val_loss: 1.1876 - val_accuracy: 0.57
25
Epoch 17/20
18/18 [=====] - 0s 16ms/step - loss: 0.5489 - accuracy: 0.9086 - val_loss: 1.2643 - val_accuracy: 0.50
72
Epoch 18/20
18/18 [=====] - 0s 16ms/step - loss: 0.5159 - accuracy: 0.9194 - val_loss: 1.1857 - val_accuracy: 0.57
25
Epoch 19/20
18/18 [=====] - 0s 17ms/step - loss: 0.4900 - accuracy: 0.9229 - val_loss: 1.3795 - val_accuracy: 0.52
17
Epoch 20/20
18/18 [=====] - 0s 16ms/step - loss: 0.5184 - accuracy: 0.8907 - val_loss: 1.2610 - val_accuracy: 0.57
25
```



Perform ONE of the following experiment below ((a), (b) or (c)) based on the last digit of your Rowan Banner ID (1 point): (a) Train the CNN using 2 other filter sizes:  $5 \times 5$  and  $7 \times 7$  for the convolution layer (i) with all other parameters unchanged (b) Train the CNN using 2 other number of filters: 4 and 16 for the convolution layer (i) with all other parameters unchanged (c) Train the CNN using 2 other number of nodes in the hidden layer (iv): 8 and 32 with all other parameters unchanged If the last digit is  $\{0, 1, 2, 3\}$ , do (a). If the last digit is  $\{4, 5, 6\}$ , do (b). If the last digit is  $\{7, 8, 9\}$ , do (c). State your Rowan Banner ID in your submission so that we know which experiment you are doing.

Plot the learning curves (i.e., x-axis: number of epochs; y-axis: training and validation accuracy -2 curves) for the classification models using the above 2 different parameter values (1 points)

BANNER ID: 916451763 Since the last digit of my banner iD is 3. Do (a)

(a) Train the CNN using 2 other filter sizes:

5 × 5 for the convolution layer (i) with all other parameters unchanged

```
In [10]: import tensorflow as tf
from tensorflow.keras import layers, models
from tensorflow.keras.optimizers.legacy import Adam as LegacyAdam
from tensorflow.keras.losses import CategoricalCrossentropy
from tensorflow.keras.preprocessing.image import ImageDataGenerator
import matplotlib.pyplot as plt

model = models.Sequential()

# Convolutional Layer with 2 other filter sizes: 5 × 5 and 7 × 7
model.add(layers.Conv2D(8, (5, 5), activation='relu', input_shape=(100, 100, 3)))
# Alternatively, you can uncomment the line below to use 7 × 7 filters

# MaxPooling Layer with 2 × 2 pool size
model.add(layers.MaxPooling2D((2, 2)))

# Flatten the Tensor
model.add(layers.Flatten())

# Hidden layer with 16 nodes for a fully connected neural network
model.add(layers.Dense(16, activation='relu'))

# Output layer has 4 nodes (since 4 classes) using 'softmax' activation function
model.add(layers.Dense(4, activation='softmax'))

model.compile(optimizer=LegacyAdam(), loss=CategoricalCrossentropy(), metrics=['accuracy'])
model.summary()

datagen = ImageDataGenerator(rescale=1./255, validation_split=0.2)

dataset_path = '/Users/sarahsamhithachella/Downloads/SarahNew/Images'

train_generator = datagen.flow_from_directory(
    dataset_path,
    target_size=(100, 100),
    batch_size=32,
    class_mode='categorical',
    subset='training'
)

validation_generator = datagen.flow_from_directory(
    dataset_path,
    target_size=(100, 100),
    batch_size=32,
    class_mode='categorical',
    subset='validation'
```

```
)  
  
history = model.fit(  
    train_generator,  
    epochs=20,  
    validation_data=validation_generator  
)  
  
import matplotlib.pyplot as plt  
  
# Plot the learning curves  
plt.plot(history.history['accuracy'], label='Training Accuracy')  
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')  
plt.xlabel('Epochs')  
plt.ylabel('Accuracy')  
plt.legend()  
plt.show()
```



Model: "sequential\_6"

Layer (type)	Output Shape	Param #
conv2d_6 (Conv2D)	(None, 96, 96, 8)	608
max_pooling2d_6 (MaxPoolin g2D)	(None, 48, 48, 8)	0
flatten_6 (Flatten)	(None, 18432)	0
dense_12 (Dense)	(None, 16)	294928
dense_13 (Dense)	(None, 4)	68

=====  
Total params: 295604 (1.13 MB)  
Trainable params: 295604 (1.13 MB)  
Non-trainable params: 0 (0.00 Byte)

Found 558 images belonging to 4 classes.

Found 138 images belonging to 4 classes.

Epoch 1/20

18/18 [=====] - 1s 31ms/step - loss: 1.3017 - accuracy: 0.3710 - val\_loss: 1.0819 - val\_accuracy: 0.5580

Epoch 2/20

18/18 [=====] - 1s 29ms/step - loss: 0.9764 - accuracy: 0.5878 - val\_loss: 0.8957 - val\_accuracy: 0.6159

Epoch 3/20

18/18 [=====] - 1s 29ms/step - loss: 0.7561 - accuracy: 0.7025 - val\_loss: 0.8469 - val\_accuracy: 0.6304

Epoch 4/20

18/18 [=====] - 1s 29ms/step - loss: 0.6190 - accuracy: 0.7814 - val\_loss: 0.7844 - val\_accuracy: 0.6522

Epoch 5/20

18/18 [=====] - 1s 30ms/step - loss: 0.4726 - accuracy: 0.8495 - val\_loss: 0.7389 - val\_accuracy: 0.7174

Epoch 6/20

18/18 [=====] - 1s 29ms/step - loss: 0.3857 - accuracy: 0.8943 - val\_loss: 0.7474 - val\_accuracy: 0.6594

Epoch 7/20

18/18 [=====] - 1s 28ms/step - loss: 0.3426 - accuracy: 0.8996 - val\_loss: 0.7668 - val\_accuracy: 0.6739

Epoch 8/20

18/18 [=====] - 1s 29ms/step - loss: 0.2542 - accuracy: 0.9570 - val\_loss: 0.8622 - val\_accuracy: 0.6739

Epoch 9/20

18/18 [=====] - 1s 29ms/step - loss: 0.1880 - accuracy: 0.9767 - val\_loss: 0.8033 - val\_accuracy: 0.63

77

Epoch 10/20

18/18 [=====] - 1s 29ms/step - loss: 0.1292 - accuracy: 0.9910 - val\_loss: 0.8020 - val\_accuracy: 0.65

22

Epoch 11/20

18/18 [=====] - 1s 29ms/step - loss: 0.1050 - accuracy: 0.9946 - val\_loss: 0.9037 - val\_accuracy: 0.65

94

Epoch 12/20

18/18 [=====] - 1s 28ms/step - loss: 0.0816 - accuracy: 0.9964 - val\_loss: 0.8750 - val\_accuracy: 0.65

94

Epoch 13/20

18/18 [=====] - 1s 30ms/step - loss: 0.0639 - accuracy: 0.9946 - val\_loss: 0.9106 - val\_accuracy: 0.68

12

Epoch 14/20

18/18 [=====] - 1s 29ms/step - loss: 0.0585 - accuracy: 0.9964 - val\_loss: 0.9149 - val\_accuracy: 0.65

94

Epoch 15/20

18/18 [=====] - 1s 29ms/step - loss: 0.0460 - accuracy: 0.9964 - val\_loss: 0.9544 - val\_accuracy: 0.67

39

Epoch 16/20

18/18 [=====] - 1s 29ms/step - loss: 0.0366 - accuracy: 0.9982 - val\_loss: 0.9511 - val\_accuracy: 0.66

67

Epoch 17/20

18/18 [=====] - 1s 29ms/step - loss: 0.0299 - accuracy: 0.9982 - val\_loss: 1.0472 - val\_accuracy: 0.65

22

Epoch 18/20

18/18 [=====] - 1s 29ms/step - loss: 0.0252 - accuracy: 1.0000 - val\_loss: 1.0587 - val\_accuracy: 0.68

12

Epoch 19/20

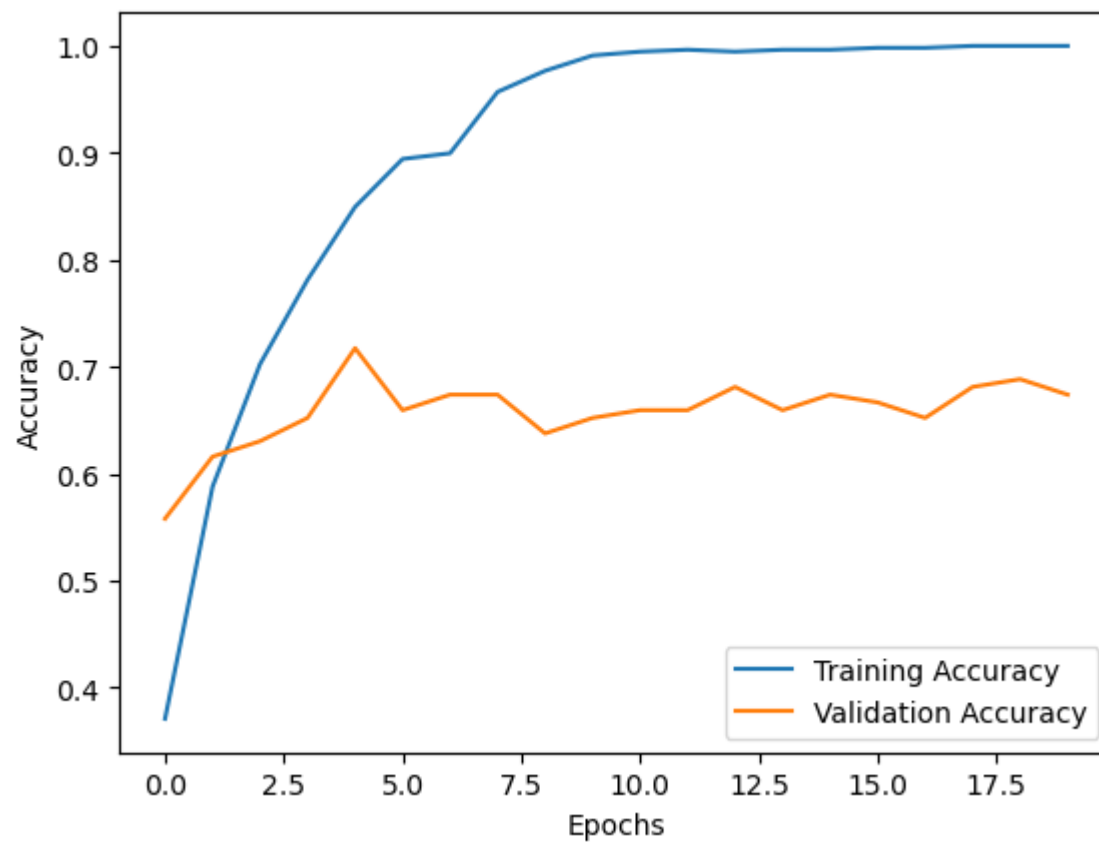
18/18 [=====] - 1s 29ms/step - loss: 0.0215 - accuracy: 1.0000 - val\_loss: 1.0160 - val\_accuracy: 0.68

84

Epoch 20/20

18/18 [=====] - 1s 30ms/step - loss: 0.0187 - accuracy: 1.0000 - val\_loss: 1.0307 - val\_accuracy: 0.67

39



(a) Train the CNN using 2 other filter sizes:

$7 \times 7$  for the convolution layer (i) with all other parameters unchanged

```
In [11]: import tensorflow as tf
from tensorflow.keras import layers, models
from tensorflow.keras.optimizers.legacy import Adam as LegacyAdam
from tensorflow.keras.losses import CategoricalCrossentropy
from tensorflow.keras.preprocessing.image import ImageDataGenerator
import matplotlib.pyplot as plt

model = models.Sequential()

model.add(layers.Conv2D(8, (7, 7), activation='relu', input_shape=(100, 100, 3)))

# MaxPooling Layer with 2 x 2 pool size
model.add(layers.MaxPooling2D((2, 2)))

# Flatten the Tensor
```

```

model.add(layers.Flatten())

# Hidden layer with 16 nodes for a fully connected neural network
model.add(layers.Dense(16, activation='relu'))

# Output layer has 4 nodes (since 4 classes) using 'softmax' activation function
model.add(layers.Dense(4, activation='softmax'))

model.compile(optimizer=LegacyAdam(), loss=CategoricalCrossentropy(), metrics=['accuracy'])
model.summary()

datagen = ImageDataGenerator(rescale=1./255, validation_split=0.2)

dataset_path = '/Users/sarahsamhithachella/Downloads/SarahNew/Images'

train_generator = datagen.flow_from_directory(
    dataset_path,
    target_size=(100, 100),
    batch_size=32,
    class_mode='categorical',
    subset='training'
)

validation_generator = datagen.flow_from_directory(
    dataset_path,
    target_size=(100, 100),
    batch_size=32,
    class_mode='categorical',
    subset='validation'
)

history = model.fit(
    train_generator,
    epochs=20,
    validation_data=validation_generator
)

import matplotlib.pyplot as plt

# Plot the learning curves
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()

```

Model: "sequential\_7"

Layer (type)	Output Shape	Param #
conv2d_7 (Conv2D)	(None, 94, 94, 8)	1184
max_pooling2d_7 (MaxPoolin g2D)	(None, 47, 47, 8)	0
flatten_7 (Flatten)	(None, 17672)	0
dense_14 (Dense)	(None, 16)	282768
dense_15 (Dense)	(None, 4)	68

=====  
Total params: 284020 (1.08 MB)  
Trainable params: 284020 (1.08 MB)  
Non-trainable params: 0 (0.00 Byte)

=====  
Found 558 images belonging to 4 classes.  
Found 138 images belonging to 4 classes.

Epoch 1/20

18/18 [=====] - 1s 47ms/step - loss: 1.4177 - accuracy: 0.3477 - val\_loss: 1.3098 - val\_accuracy: 0.4420

Epoch 2/20

18/18 [=====] - 1s 45ms/step - loss: 1.2172 - accuracy: 0.3728 - val\_loss: 1.1820 - val\_accuracy: 0.3623

Epoch 3/20

18/18 [=====] - 1s 43ms/step - loss: 1.1226 - accuracy: 0.4462 - val\_loss: 1.1599 - val\_accuracy: 0.3913

Epoch 4/20

18/18 [=====] - 1s 43ms/step - loss: 1.0635 - accuracy: 0.4803 - val\_loss: 1.1818 - val\_accuracy: 0.5000

Epoch 5/20

18/18 [=====] - 1s 43ms/step - loss: 0.9948 - accuracy: 0.5538 - val\_loss: 1.0836 - val\_accuracy: 0.5290

Epoch 6/20

18/18 [=====] - 1s 44ms/step - loss: 0.8354 - accuracy: 0.6613 - val\_loss: 0.9492 - val\_accuracy: 0.5870

Epoch 7/20

18/18 [=====] - 1s 43ms/step - loss: 0.6750 - accuracy: 0.7509 - val\_loss: 1.0837 - val\_accuracy: 0.5290

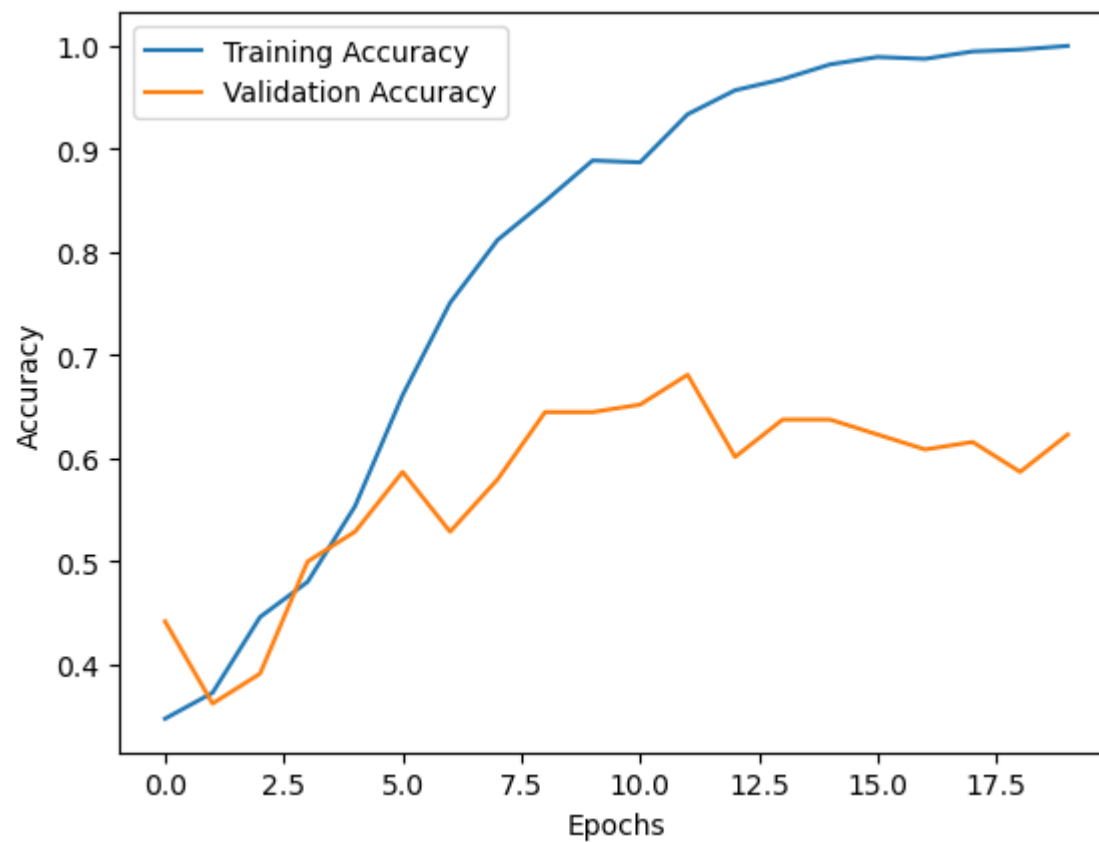
Epoch 8/20

18/18 [=====] - 1s 43ms/step - loss: 0.5814 - accuracy: 0.8118 - val\_loss: 1.0857 - val\_accuracy: 0.5797

Epoch 9/20

18/18 [=====] - 1s 43ms/step - loss: 0.5004 - accuracy: 0.8495 - val\_loss: 0.9227 - val\_accuracy: 0.64

49  
Epoch 10/20  
18/18 [=====] - 1s 44ms/step - loss: 0.4080 - accuracy: 0.8889 - val\_loss: 0.8945 - val\_accuracy: 0.64  
49  
Epoch 11/20  
18/18 [=====] - 1s 44ms/step - loss: 0.3656 - accuracy: 0.8871 - val\_loss: 0.9764 - val\_accuracy: 0.65  
22  
Epoch 12/20  
18/18 [=====] - 1s 43ms/step - loss: 0.2946 - accuracy: 0.9337 - val\_loss: 0.9842 - val\_accuracy: 0.68  
12  
Epoch 13/20  
18/18 [=====] - 1s 44ms/step - loss: 0.2254 - accuracy: 0.9570 - val\_loss: 1.1202 - val\_accuracy: 0.60  
14  
Epoch 14/20  
18/18 [=====] - 1s 43ms/step - loss: 0.1818 - accuracy: 0.9677 - val\_loss: 1.0346 - val\_accuracy: 0.63  
77  
Epoch 15/20  
18/18 [=====] - 1s 43ms/step - loss: 0.1321 - accuracy: 0.9821 - val\_loss: 1.1495 - val\_accuracy: 0.63  
77  
Epoch 16/20  
18/18 [=====] - 1s 45ms/step - loss: 0.1059 - accuracy: 0.9892 - val\_loss: 1.1922 - val\_accuracy: 0.62  
32  
Epoch 17/20  
18/18 [=====] - 1s 43ms/step - loss: 0.0876 - accuracy: 0.9875 - val\_loss: 1.2454 - val\_accuracy: 0.60  
87  
Epoch 18/20  
18/18 [=====] - 1s 43ms/step - loss: 0.0785 - accuracy: 0.9946 - val\_loss: 1.2257 - val\_accuracy: 0.61  
59  
Epoch 19/20  
18/18 [=====] - 1s 43ms/step - loss: 0.0640 - accuracy: 0.9964 - val\_loss: 1.4161 - val\_accuracy: 0.58  
70  
Epoch 20/20  
18/18 [=====] - 1s 43ms/step - loss: 0.0422 - accuracy: 1.0000 - val\_loss: 1.3145 - val\_accuracy: 0.62  
32



Describe and discuss what you observe by comparing the performance of the first model and the other two models you constructed in (a), (b) or (c) (depending on which one you did). Are there model overfit or underfit or just right? (1 point)

Model: "sequential\_5"

Architecture: Convolutional Neural Network with 1 convolutional layer, max pooling, and 2 dense layers.

Total params: 307,636

Training accuracy: ~89.1%

Validation accuracy: ~57.3%

Loss: After about 12 epochs, the validation loss slightly increases while the training loss gradually decreases. So, there might be overfitting.

Model: "sequential\_6"

Architecture: CNN with 1 convolutional layer, max pooling, and 2 dense layers.

Total params: 295,604

Training accuracy: ~100%

Validation accuracy: ~67.4%

Loss: Both training and validation losses decrease consistently. This indicates a good fit and no signs of overfitting.

## Model: "sequential\_7"

Architecture: CNN with 1 convolutional layer, max pooling, and 2 dense layers.

Total params: 284,020

Training accuracy: ~100%

Validation accuracy: ~62.3%

Loss: Similar to Model 6, both training and validation losses decrease consistently. This also indicates a good fit and no signs of overfitting.

## Is the model overfit or underfit or just right? :

(Model 5): As the training accuracy is significantly higher than the validation accuracy, and the validation loss increases after a certain point, model 5 shows signs of overfitting.

Model 5 has the highest number of parameters, which might contribute to overfitting.

Model 5 lags behind in terms of validation accuracy.

(Models 6 and 7): These models do not exhibit clear signs of overfitting. Both training and validation accuracies are high, and losses continue to decrease.

Models 6 and 7 have slightly fewer parameters but still achieve high accuracy, indicating that they might be more efficient in this context.

## Validation Accuracy:

Model 6 has the highest validation accuracy, followed closely by Model 7.

Model 5 lags behind in terms of validation accuracy.

## References:

[Java point: Association Rule Learning](#)



[Association Rules With Python](#)

[CNN Image Classification](#)

[Heatmap using Seaborn](#)

[Simple MNIST Convnet](#)

[Association Rules Guide](#)

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