mlp

September 9, 2025

[12]:
```python
import os
import numpy as np
import pandas as pd
from PIL import Image
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, label_binarize
from sklearn.metrics import (
    classification_report, confusion_matrix,
    accuracy_score, roc_curve, auc
)

import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, TensorDataset

import matplotlib.pyplot as plt
import seaborn as sns
```

[13]:
```python
csv_path = "archive/english.csv"
df = pd.read_csv(csv_path)

ROOT = "archive"
IMG_SIZE = (28, 28)  # width, height

images, labels, missing = [], [], []
for idx, row in df.iterrows():
    img_rel = row["image"]
    label_raw = row["label"]
    img_path = os.path.join(ROOT, img_rel)

    if not os.path.exists(img_path):
        missing.append(img_path)
        continue

    im = Image.open(img_path).convert("L")
    im = im.resize(IMG_SIZE)
    arr = np.asarray(im, dtype=np.float32).flatten() / 255.0  # normalize [0,1]
```

```
    images.append(arr)
    labels.append(label_raw)

print("Missing files:", len(missing))

X = np.vstack(images)  # (N, D)
y_raw = np.array(labels)
print("Loaded X:", X.shape, " y:", y_raw.shape)
```

```
Missing files: 0
Loaded X: (3410, 784)  y: (3410,)
```

[14]:
```
# Encode to integers 0..C-1
le = LabelEncoder()
y = le.fit_transform(y_raw)

# Stratified split -> train, validation, test
RNG_SEED = 42
X_train_full, X_test, y_train_full, y_test = train_test_split(
    X, y, test_size=0.2, stratify=y, random_state=RNG_SEED
)

X_train, X_val, y_train, y_val = train_test_split(
    X_train_full, y_train_full, test_size=0.2,
    stratify=y_train_full, random_state=RNG_SEED
)

print("Shapes -> train:", X_train.shape, "val:", X_val.shape, "test:", X_test.
 ↪shape)
print("Num classes:", len(le.classes_))
```

```
Shapes -> train: (2182, 784) val: (546, 784) test: (682, 784)
Num classes: 62
```

[15]:
```
X_train_t = torch.tensor(X_train, dtype=torch.float32)
y_train_t = torch.tensor(y_train, dtype=torch.long)
X_val_t   = torch.tensor(X_val, dtype=torch.float32)
y_val_t   = torch.tensor(y_val, dtype=torch.long)
X_test_t  = torch.tensor(X_test, dtype=torch.float32)
y_test_t  = torch.tensor(y_test, dtype=torch.long)

def get_loader(X, y, batch_size):
    ds = TensorDataset(X, y)
    return DataLoader(ds, batch_size=batch_size, shuffle=True)
```

[16]:
```
class MLP(nn.Module):
```

```
    def __init__(self, input_dim, hidden_dim, output_dim, activation="relu",␣
↪num_hidden=1):
        super().__init__()
        act_fn = {"relu": nn.ReLU(), "tanh": nn.Tanh(), "sigmoid": nn.
↪Sigmoid()}[activation]

        layers = []
        layers.append(nn.Linear(input_dim, hidden_dim))
        layers.append(act_fn)

        if num_hidden == 2:
            layers.append(nn.Linear(hidden_dim, hidden_dim))
            layers.append(act_fn)

        layers.append(nn.Linear(hidden_dim, output_dim))
        self.net = nn.Sequential(*layers)

    def forward(self, x):
        return self.net(x)
```

[17]:
```
def train_model(params):
    batch_size, lr, hidden_dim, activation, optimizer_name, num_hidden = params

    train_loader = get_loader(X_train_t, y_train_t, batch_size)
    val_loader   = get_loader(X_val_t, y_val_t, batch_size)

    model = MLP(X_train.shape[1], hidden_dim, len(le.classes_), activation,␣
↪num_hidden)
    criterion = nn.CrossEntropyLoss()

    if optimizer_name == "sgd":
        optimizer = optim.SGD(model.parameters(), lr=lr)
    else:
        optimizer = optim.Adam(model.parameters(), lr=lr)

    history = {"train_loss": [], "val_loss": [], "val_acc": []}
    EPOCHS = 20

    for epoch in range(EPOCHS):
        model.train()
        train_loss = 0
        for xb, yb in train_loader:
            optimizer.zero_grad()
            out = model(xb)
            loss = criterion(out, yb)
            loss.backward()
            optimizer.step()
```

```python
            train_loss += loss.item()

        # validation
        model.eval()
        val_loss, correct = 0, 0
        with torch.no_grad():
            for xb, yb in val_loader:
                out = model(xb)
                loss = criterion(out, yb)
                val_loss += loss.item()
                preds = out.argmax(dim=1)
                correct += (preds == yb).sum().item()
        acc = correct / len(val_loader.dataset)

        history["train_loss"].append(train_loss/len(train_loader))
        history["val_loss"].append(val_loss/len(val_loader))
        history["val_acc"].append(acc)

    return model, history
```

[11]:

```python
search_space = [
    (bs, lr, hd, act, opt, nh)
    for bs in [32, 64, 128]             # batch sizes
    for lr in [0.1, 0.01, 0.001]        # learning rates
    for hd in [128, 256]                # hidden layer size
    for act in ["relu", "tanh", "sigmoid"]  # activations
    for opt in ["sgd", "adam"]          # optimizers
    for nh in [1, 2]                    # number of hidden layers
]

best_acc, best_params, best_model, best_history = 0, None, None, None

for params in search_space:
    model, hist = train_model(params)
    final_acc = hist["val_acc"][-1]

    if final_acc > best_acc:
        best_acc = final_acc
        best_params = params
        best_model = model
        best_history = hist

print("\nBest Params:", best_params)
print("Best Val Accuracy:", best_acc)
```

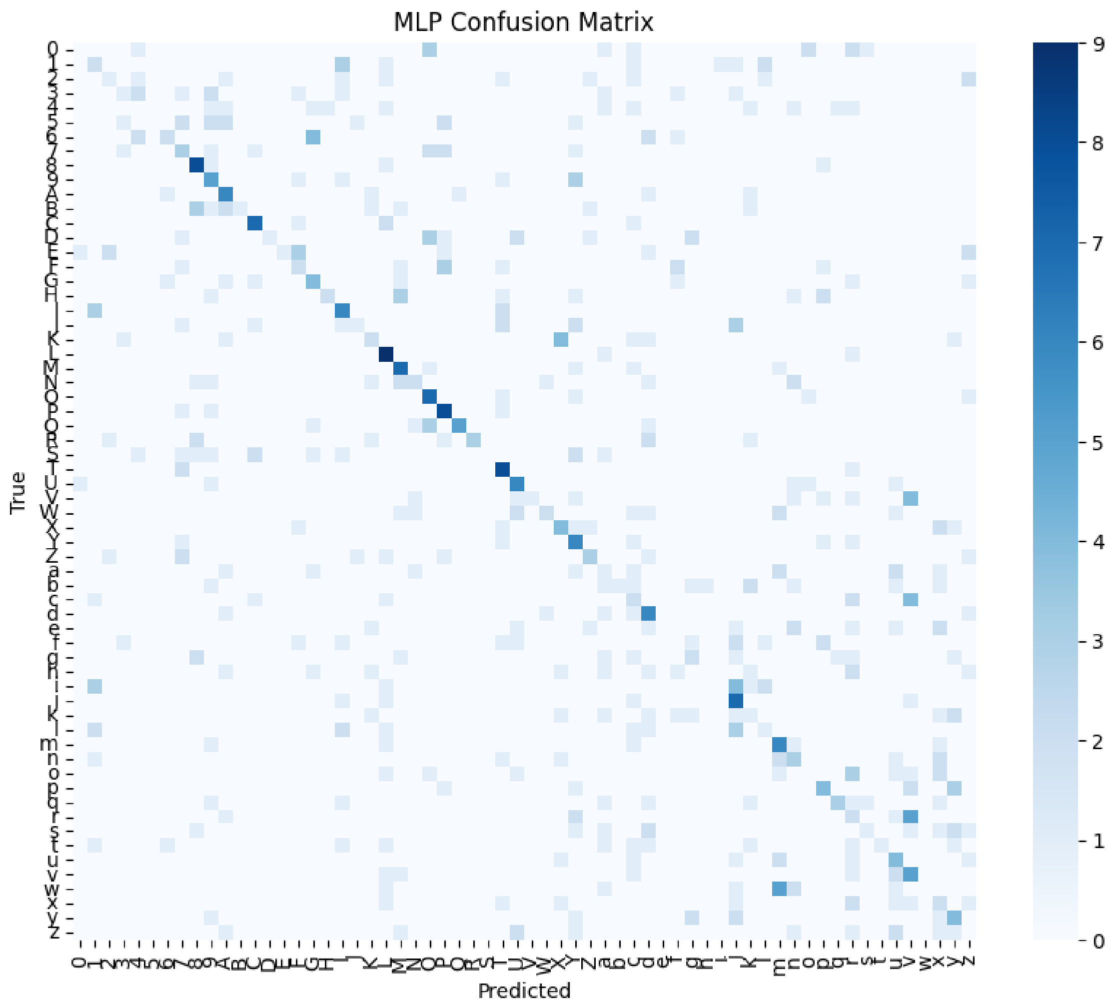
```
Best Params: (32, 0.001, 256, 'sigmoid', 'adam', 1)
Best Val Accuracy: 0.30036630036630035
```

[18]:
```python
best_model.eval()
with torch.no_grad():
    preds = best_model(X_test_t).argmax(dim=1).numpy()

print("\nMLP Test Accuracy:", accuracy_score(y_test, preds))
print("\nClassification Report:\n", classification_report(y_test, preds,
    target_names=le.classes_))

# Confusion Matrix
cm = confusion_matrix(y_test, preds)
plt.figure(figsize=(10,8))
sns.heatmap(cm, cmap="Blues", xticklabels=le.classes_, yticklabels=le.classes_,
    annot=False)
plt.xlabel("Predicted")
plt.ylabel("True")
plt.title("MLP Confusion Matrix")
plt.show()
```

```
MLP Test Accuracy: 0.2668621700879765

Classification Report:
               precision    recall  f1-score   support

           0       0.00      0.00      0.00        11
           1       0.15      0.18      0.17        11
           2       0.20      0.09      0.12        11
           3       0.20      0.09      0.12        11
           4       0.00      0.00      0.00        11
           5       0.00      0.00      0.00        11
           6       0.40      0.18      0.25        11
           7       0.19      0.27      0.22        11
           8       0.44      0.73      0.55        11
           9       0.23      0.45      0.30        11
           A       0.32      0.55      0.40        11
           B       1.00      0.09      0.17        11
           C       0.54      0.64      0.58        11
           D       1.00      0.09      0.17        11
           E       1.00      0.09      0.17        11
           F       0.20      0.18      0.19        11
           G       0.31      0.36      0.33        11
           H       0.67      0.18      0.29        11
           I       0.30      0.55      0.39        11
           J       0.33      0.09      0.14        11
           K       0.22      0.18      0.20        11
           L       0.35      0.82      0.49        11
           M       0.37      0.64      0.47        11
           N       0.33      0.18      0.24        11
```

```
           O       0.35      0.64      0.45        11
           P       0.40      0.73      0.52        11
           Q       0.83      0.45      0.59        11
           R       1.00      0.27      0.43        11
           S       0.00      0.00      0.00        11
           T       0.35      0.73      0.47        11
           U       0.38      0.55      0.44        11
           V       1.00      0.09      0.17        11
           W       0.50      0.18      0.27        11
           X       0.31      0.36      0.33        11
           Y       0.22      0.55      0.32        11
           Z       0.38      0.27      0.32        11
           a       0.07      0.09      0.08        11
           b       1.00      0.09      0.17        11
           c       0.10      0.18      0.12        11
           d       0.24      0.55      0.33        11
           e       0.00      0.00      0.00        11
           f       0.00      0.00      0.00        11
           g       0.22      0.18      0.20        11
           h       0.00      0.00      0.00        11
           i       0.00      0.00      0.00        11
           j       0.24      0.64      0.35        11
           k       0.09      0.09      0.09        11
           l       0.14      0.09      0.11        11
           m       0.29      0.55      0.38        11
           n       0.19      0.27      0.22        11
           o       0.00      0.00      0.00        11
           p       0.33      0.36      0.35        11
           q       0.60      0.27      0.38        11
           r       0.08      0.18      0.11        11
           s       0.33      0.09      0.14        11
           t       1.00      0.09      0.17        11
           u       0.21      0.36      0.27        11
           v       0.21      0.45      0.29        11
           w       0.00      0.00      0.00        11
           x       0.11      0.18      0.14        11
           y       0.25      0.36      0.30        11
           z       0.00      0.00      0.00        11

    accuracy                           0.27       682
   macro avg       0.33      0.27      0.23       682
weighted avg       0.33      0.27      0.23       682

/home/pranesh/Downloads/ML Lab/.venv/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1731: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
```

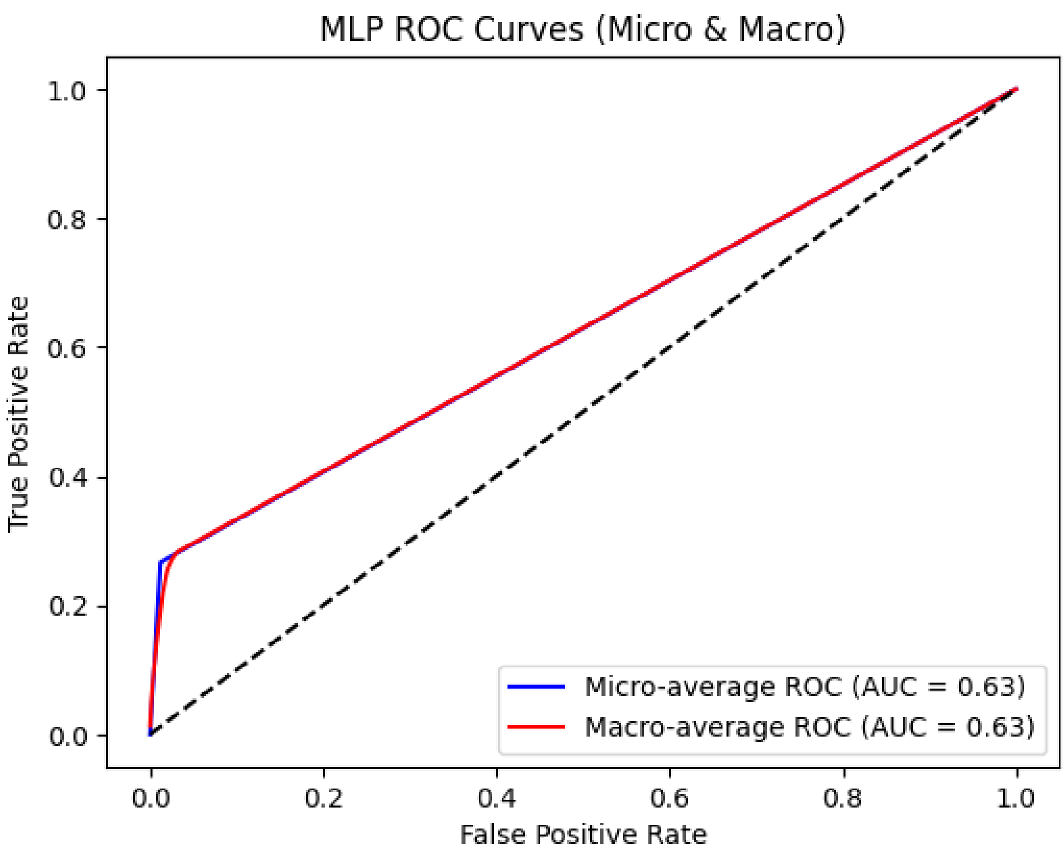
```
  _warn_prf(average, modifier, f"{metric.capitalize()} is", result.shape[0])
/home/pranesh/Downloads/ML Lab/.venv/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1731: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", result.shape[0])
/home/pranesh/Downloads/ML Lab/.venv/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1731: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", result.shape[0])
```



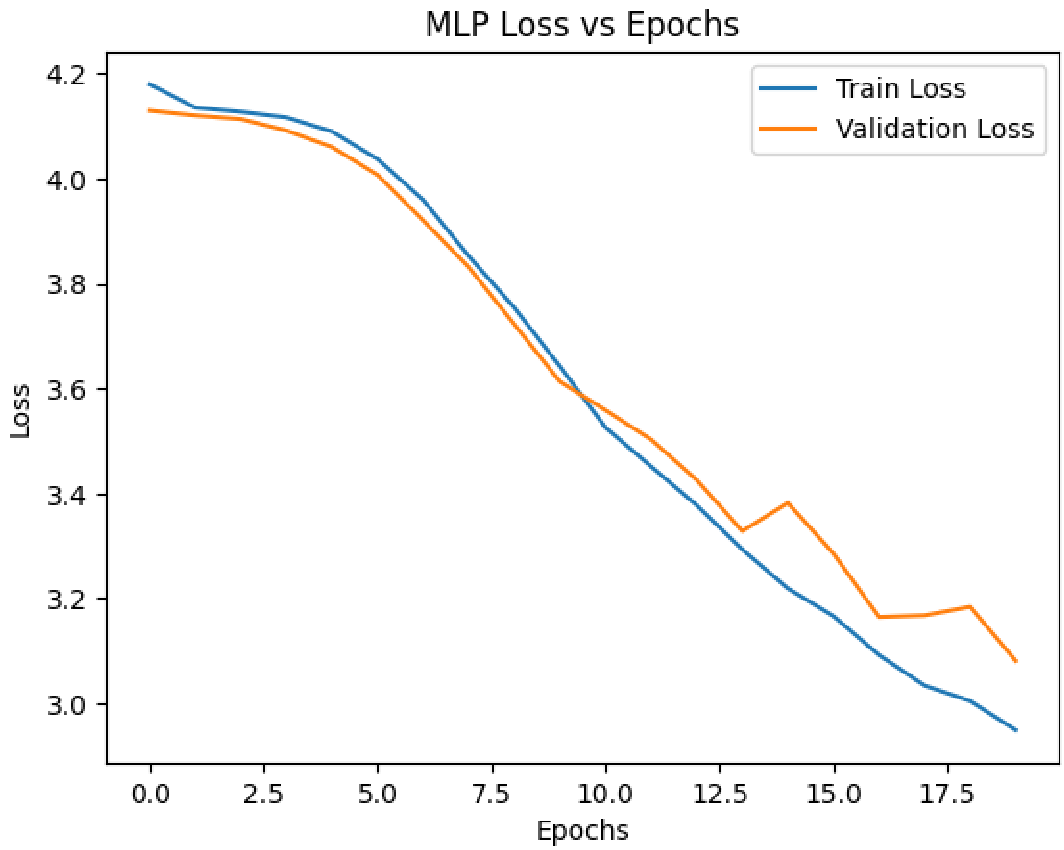
[19]:

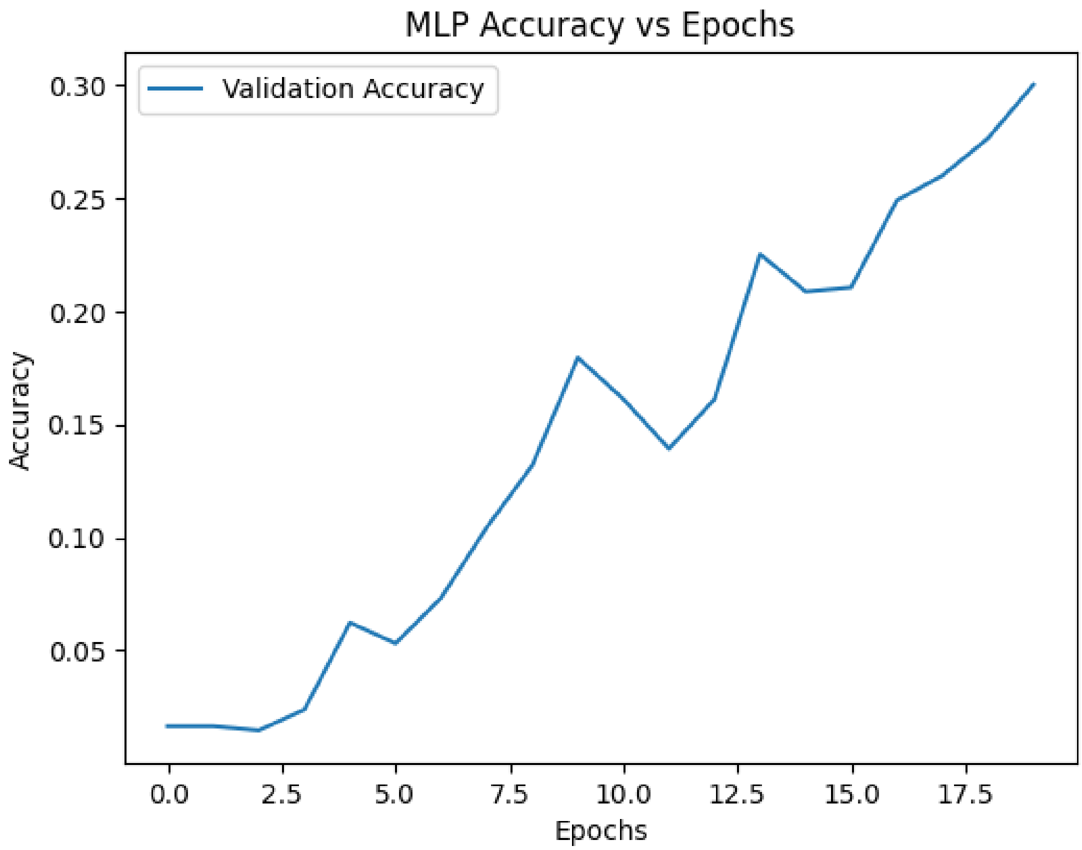
```python
y_test_bin = label_binarize(y_test, classes=np.arange(len(le.classes_)))
preds_bin = label_binarize(preds, classes=np.arange(len(le.classes_)))

fpr_micro, tpr_micro, _ = roc_curve(y_test_bin.ravel(), preds_bin.ravel())
```

```python
roc_auc_micro = auc(fpr_micro, tpr_micro)

fpr_dict, tpr_dict, roc_auc_dict = {}, {}, {}
for i in range(len(le.classes_)):
    fpr_dict[i], tpr_dict[i], _ = roc_curve(y_test_bin[:, i], preds_bin[:, i])
    roc_auc_dict[i] = auc(fpr_dict[i], tpr_dict[i])

all_fpr = np.unique(np.concatenate([fpr_dict[i] for i in range(len(le.classes_))]))
mean_tpr = np.zeros_like(all_fpr)
for i in range(len(le.classes_)):
    mean_tpr += np.interp(all_fpr, fpr_dict[i], tpr_dict[i])
mean_tpr /= len(le.classes_)
roc_auc_macro = auc(all_fpr, mean_tpr)

plt.figure()
plt.plot(fpr_micro, tpr_micro, label=f"Micro-average ROC (AUC = {roc_auc_micro:.2f})", color="blue")
plt.plot(all_fpr, mean_tpr, label=f"Macro-average ROC (AUC = {roc_auc_macro:.2f})", color="red")
plt.plot([0, 1], [0, 1], "k--")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("MLP ROC Curves (Micro & Macro)")
plt.legend(loc="lower right")
plt.show()
```



[20]:
```
plt.figure()
plt.plot(best_history["train_loss"], label="Train Loss")
plt.plot(best_history["val_loss"], label="Validation Loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.title("MLP Loss vs Epochs")
plt.legend()
plt.show()

plt.figure()
plt.plot(best_history["val_acc"], label="Validation Accuracy")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.title("MLP Accuracy vs Epochs")
plt.legend()
plt.show()
```


MLP Loss vs Epochs
Train Loss
Validation Loss
Loss
Epochs
4.2
4.0
3.8
3.6
3.4
3.2
3.0
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5


MLP Accuracy vs Epochs
Validation Accuracy
0.30
0.25
0.20
0.15
0.10
0.05
Accuracy
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
Epochs