Question 1

In [1]:

```
import pyspark
from pyspark.sql import SparkSession, SQLContext
from pyspark.ml import Pipeline,Transformer
from pyspark.ml.feature import Imputer,StandardScaler,StringIndexer,OneHotEncoder, Vecto

from pyspark.sql.functions import *
from pyspark.sql.types import *
import numpy as np

col_names = ["duration","protocol_type","service","flag","src_bytes",
"dst_bytes","land","wrong_fragment","urgent","hot","num_failed_logins",
"logged_in","num_compromised","root_shell","su_attempted","num_root",
"num_file_creations","num_shells","num_access_files","num_outbound_cmds",
"is_host_login","is_guest_login","count","srv_count","serror_rate",
"srv_serror_rate","rerror_rate","srv_rerror_rate","same_srv_rate",
"diff_srv_rate","srv_diff_host_rate","dst_host_count","dst_host_srv_count",
"dst_host_same_srv_rate","dst_host_diff_srv_rate","dst_host_same_src_port_rate",
"dst_host_srv_diff_host_rate","dst_host_serror_rate","dst_host_srv_serror_rate",
"dst_host_rerror_rate","dst_host_srv_rerror_rate","class","difficulty"]

nominal_cols = ['protocol_type','service','flag']
binary_cols = ['land', 'logged_in', 'root_shell', 'su_attempted', 'is_host_login',
'is_guest_login']
continuous_cols = ['duration' ,'src_bytes', 'dst_bytes', 'wrong_fragment' ,'urgent', 'ho
'num_failed_logins', 'num_compromised', 'num_root' ,'num_file_creations',
'num_shells', 'num_access_files', 'num_outbound_cmds', 'count' ,'srv_count',
'serror_rate', 'srv_serror_rate' ,'rerror_rate' ,'srv_rerror_rate',
'same_srv_rate', 'diff_srv_rate', 'srv_diff_host_rate' ,'dst_host_count',
'dst_host_srv_count' ,'dst_host_same_srv_rate' ,'dst_host_diff_srv_rate',
'dst_host_same_src_port_rate' ,'dst_host_srv_diff_host_rate',
'dst_host_serror_rate' ,'dst_host_srv_serror_rate', 'dst_host_rerror_rate',
'dst_host_srv_rerror_rate']

attack_category = ['normal', 'DOS', 'R2L', 'U2R', 'probe']
normal = ['normal']
DOS = ['apache2','back','land','neptune','mailbomb','pod','processtable','smurf','teardr
R2L = ['ftp_write','guess_passwd','httptunnel','imap','multihop','named','phf','sendmail
U2R = ['buffer_overflow','loadmodule','perl','ps','rootkit','sqlattack','xterm']
probe = ['ipsweep','mscan','nmap','portsweep','saint','satan']

class OutcomeCreater(Transformer): # this defines a transformer that creates the outcome

    def __init__(self):
        super().__init__()

    def _transform(self, dataset):
        label_to_binary = udf(lambda name: 0.0 if name == 'normal' else 1.0 if name in D
        label_to_category = udf(lambda name: attack_category[0] if name == 0.0 else atta
        output_df = dataset.withColumn('outcome', label_to_binary(col('class'))).drop("c
        output_df = output_df.withColumn('outcome', col('outcome').cast(DoubleType()))
        output_df = output_df.withColumn('outcome_category',label_to_category(col('outco
        output_df = output_df.withColumn('outcome_category', col('outcome_category').cas
        output_df = output_df.drop('difficulty')
        return output_df

class FeatureTypeCaster(Transformer): # this transformer will cast the columns as approp
    def __init__(self):
        super().__init__()

    def _transform(self, dataset):
        output_df = dataset
```

```
        for col_name in binary_cols + continuous_cols:
            output_df = output_df.withColumn(col_name,col(col_name).cast(DoubleType()))

        return output_df
class ColumnDropper(Transformer): # this transformer drops unnecessary columns
    def __init__(self, columns_to_drop = None):
        super().__init__()
        self.columns_to_drop=columns_to_drop
    def _transform(self, dataset):
        output_df = dataset
        for col_name in self.columns_to_drop:
            output_df = output_df.drop(col_name)
        return output_df

def get_preprocess_pipeline():
    # Stage where columns are casted as appropriate types
    stage_typecaster = FeatureTypeCaster()

    # Stage where nominal columns are transformed to index columns using StringIndexer
    nominal_id_cols = [x+"_index" for x in nominal_cols]
    nominal_onehot_cols = [x+"_encoded" for x in nominal_cols]
    stage_nominal_indexer = StringIndexer(inputCols = nominal_cols, outputCols = nominal

    # Stage where the index columns are further transformed using OneHotEncoder
    stage_nominal_onehot_encoder = OneHotEncoder(inputCols=nominal_id_cols, outputCols=n

    # Stage where all relevant features are assembled into a vector (and dropping a few)
    feature_cols = continuous_cols+binary_cols+nominal_onehot_cols
    corelated_cols_to_remove = ["dst_host_serror_rate","srv_serror_rate","dst_host_srv_s
                    "srv_rerror_rate","dst_host_rerror_rate","dst_host_srv_rerror_rate"
    for col_name in corelated_cols_to_remove:
        feature_cols.remove(col_name)
    stage_vector_assembler = VectorAssembler(inputCols=feature_cols, outputCol="vectoriz

    # Stage where we scale the columns
    stage_scaler = StandardScaler(inputCol= 'vectorized_features', outputCol= 'features'


    # Stage for creating the outcome column representing whether there is attack
    stage_outcome = OutcomeCreater()

    # Removing all unnecessary columbs, only keeping the 'features' and 'outcome' column
    stage_column_dropper = ColumnDropper(columns_to_drop = nominal_cols+nominal_id_cols+
        nominal_onehot_cols+ binary_cols + continuous_cols + ['vectorized_features'])
    # Connect the columns into a pipeline
    pipeline = Pipeline(stages=[stage_typecaster,stage_nominal_indexer,stage_nominal_one
        stage_vector_assembler,stage_scaler,stage_outcome,stage_column_dropper])
    return pipeline


import os
import sys

os.environ['PYSPARK_PYTHON'] = sys.executable
os.environ['PYSPARK_DRIVER_PYTHON'] = sys.executable

spark = SparkSession.builder \
    .master("local[*]") \
    .appName("SystemsToolChains") \
    .getOrCreate()

nslkdd_raw = spark.read.csv('/Users/kiranprasadjp/Downloads/NSL-KDD/KDDTrain+.txt',heade
nslkdd_test_raw = spark.read.csv('/Users/kiranprasadjp/Downloads/NSL-KDD/KDDTest+.txt',h

preprocess_pipeline = get_preprocess_pipeline()
preprocess_pipeline_model = preprocess_pipeline.fit(nslkdd_raw)
```

```
nslkdd_df = preprocess_pipeline_model.transform(nslkdd_raw)
nslkdd_df_test = preprocess_pipeline_model.transform(nslkdd_test_raw)
```

```
Setting default log level to "WARN".
To adjust logging level use sc.setLogLevel(newLevel). For SparkR, use setLogLevel(newLev
el).
23/11/09 23:33:04 WARN NativeCodeLoader: Unable to load native-hadoop library for your p
latform... using builtin-java classes where applicable
23/11/09 23:33:08 WARN SparkStringUtils: Truncated the string representation of a plan s
ince it was too large. This behavior can be adjusted by setting 'spark.sql.debug.maxToSt
ringFields'.
```

In [2]:

```
nslkdd_df.printSchema()
nslkdd_df.show()
```

```
root
 |-- features: vector (nullable = true)
 |-- outcome: double (nullable = true)
 |-- outcome_category: string (nullable = true)

+--------------------+-------+----------------+
|            features|outcome|outcome_category|
+--------------------+-------+----------------+
|(113,[1,13,14,17,...|    0.0|          normal|
|(113,[1,13,14,17,...|    0.0|          normal|
|(113,[13,14,15,17...|    1.0|             DOS|
|(113,[1,2,13,14,1...|    0.0|          normal|
|(113,[1,2,13,14,1...|    0.0|          normal|
|(113,[13,14,16,17...|    1.0|             DOS|
|(113,[13,14,15,17...|    1.0|             DOS|
|(113,[13,14,15,17...|    1.0|             DOS|
|(113,[13,14,15,17...|    1.0|             DOS|
|(113,[13,14,15,17...|    1.0|             DOS|
|(113,[13,14,16,17...|    1.0|             DOS|
|(113,[13,14,15,17...|    1.0|             DOS|
|(113,[1,2,13,14,1...|    0.0|          normal|
|(113,[1,13,14,17,...|    2.0|             R2L|
|(113,[13,14,15,18...|    1.0|             DOS|
|(113,[13,14,15,17...|    1.0|             DOS|
|(113,[1,2,13,14,1...|    0.0|          normal|
|(113,[1,13,14,17,...|    4.0|           probe|
|(113,[1,2,13,14,1...|    0.0|          normal|
|(113,[1,2,13,14,1...|    0.0|          normal|
+--------------------+-------+----------------+
only showing top 20 rows
```

In [3]:

```
import pyspark
from pyspark.sql import SparkSession, SQLContext
from pyspark.ml import Pipeline, Transformer
from pyspark.ml.feature import Imputer, StandardScaler, StringIndexer, OneHotEncoder, Ve
from pyspark.sql.functions import *
from pyspark.sql.types import *
import numpy as np
import pandas as pd
import torch
from torch.utils.data import Dataset, DataLoader, TensorDataset

# Convert Spark DataFrames to Pandas DataFrames
nslkdd_pd = nslkdd_df.toPandas()
nslkdd_test_pd = nslkdd_df_test.toPandas()

# Split the data into training, validation, and testing sets
# 50% of KDDTest+ for validation and the remaining 50% for testing
```

```
split_ratio = 0.5
split_index = int(len(nslkdd_test_pd) * split_ratio)

validation_data = nslkdd_test_pd[:split_index]
test_data = nslkdd_test_pd[split_index:]
```

In [4]:
```
x_train = torch.from_numpy(np.array(nslkdd_pd['features'].values.tolist(),np.float32))
y_train = torch.from_numpy(np.array(nslkdd_pd['outcome'].values.tolist(),np.int64))
x_validate = torch.from_numpy(np.array(validation_data['features'].values.tolist(),np.fl
y_validate = torch.from_numpy(np.array(validation_data['outcome'].values.tolist(),np.int
x_test = torch.from_numpy(np.array(test_data['features'].values.tolist(),np.float32))
y_test = torch.from_numpy(np.array(test_data['outcome'].values.tolist(),np.int64))
```

Question 2

In [5]:
```
from torch.utils.data import Dataset, DataLoader, TensorDataset

class MyDataset(Dataset):
    def __init__(self,x,y):
        self.x = x
        self.y = y
    def __len__(self):
        return self.x.shape[0]
    def __getitem__(self,idx):
        return (self.x[idx],self.y[idx])

train_dataset = MyDataset(x_train,y_train)
validate_dataset = MyDataset(x_validate,y_validate)
test_dataset = MyDataset(x_test,y_test)
```

In [6]:
```
import torch.nn as nn

class myMultilayerPerceptron(nn.Module):
    def __init__(self,input_dm,output_dm):
        super().__init__()
        self.sequential = nn.Sequential(
            nn.Linear(input_dm,226),
            nn.Tanh(),
            nn.Linear(226,113),
            nn.Tanh(),
            nn.Linear(113,56),
            nn.Tanh(),
            nn.Linear(56,28),
            nn.ReLU(),
            nn.Linear(28,output_dm)
        )
    def forward(self,x):
        y = self.sequential(x)
        return y
```

In [7]:
```
mymodel = myMultilayerPerceptron(x_train.shape[1],5)
print(mymodel)
```

```
myMultilayerPerceptron(
  (sequential): Sequential(
    (0): Linear(in_features=113, out_features=226, bias=True)
    (1): Tanh()
    (2): Linear(in_features=226, out_features=113, bias=True)
    (3): Tanh()
    (4): Linear(in_features=113, out_features=56, bias=True)
    (5): Tanh()
```

```
    (6): Linear(in_features=56, out_features=28, bias=True)
    (7): ReLU()
    (8): Linear(in_features=28, out_features=5, bias=True)
  )
)
```

Question 3 (Note: Metric chosen = accuracy)

In [8]:
```
# hyperparameters
lr = 0.05
batch_size = 64
N_epochs = 10

loss_fun = nn.CrossEntropyLoss()

train_dataloader = DataLoader(train_dataset, batch_size = batch_size, shuffle = True)
validate_dataloader = DataLoader(validate_dataset, batch_size = batch_size, shuffle = Tr

# Adam Optimizer
optimizer = torch.optim.Adam(mymodel.parameters(),lr = lr)

losses = []
accuracies = []

validate_losses = []
validate_accuracies = []

current_best_accuracy = 0.0

import numpy as np
for epoch in range(N_epochs):

    batch_loss = []
    batch_accuracy = []

    for x_batch,y_batch in train_dataloader:
        prediction_score = mymodel(x_batch)
        loss = loss_fun(prediction_score,y_batch)
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
        batch_loss.append(loss.detach().numpy())
        prediction_label = torch.argmax(prediction_score.detach(),dim=1).numpy()
        batch_accuracy.append(np.sum(prediction_label == y_batch.numpy())/x_batch.shape[

    validate_batch_loss = []
    validate_batch_accuracy = []

    for x_batch,y_batch in validate_dataloader:
        prediction_score = mymodel(x_batch)
        loss = loss_fun(prediction_score,y_batch)
        validate_batch_loss.append(loss.detach())
        prediction_label = torch.argmax(prediction_score.detach(),dim=1).numpy()
        validate_batch_accuracy.append(np.sum(prediction_label == y_batch.numpy())/x_bat

    losses.append(np.mean(np.array(batch_loss)))
    validate_losses.append(np.mean(np.array(validate_batch_loss)))

    accuracies.append(np.mean(np.array(batch_accuracy)))
    validate_accuracies.append(np.mean(np.array(validate_batch_accuracy)))

    print(f"Epoch={epoch},train_loss={losses[-1]},validate_loss={validate_losses[-1]}")
    print(f"Train_accuracy={np.round(accuracies[-1]*100,2)}%,validate_accuracy={np.round
```

```python
    if validate_accuracies[-1]>current_best_accuracy:
        print("Current epoch is best so far, saving model...")
        torch.save(mymodel.state_dict(),'current_best_model')
        current_best_accuracy = validate_accuracies[-1]
```

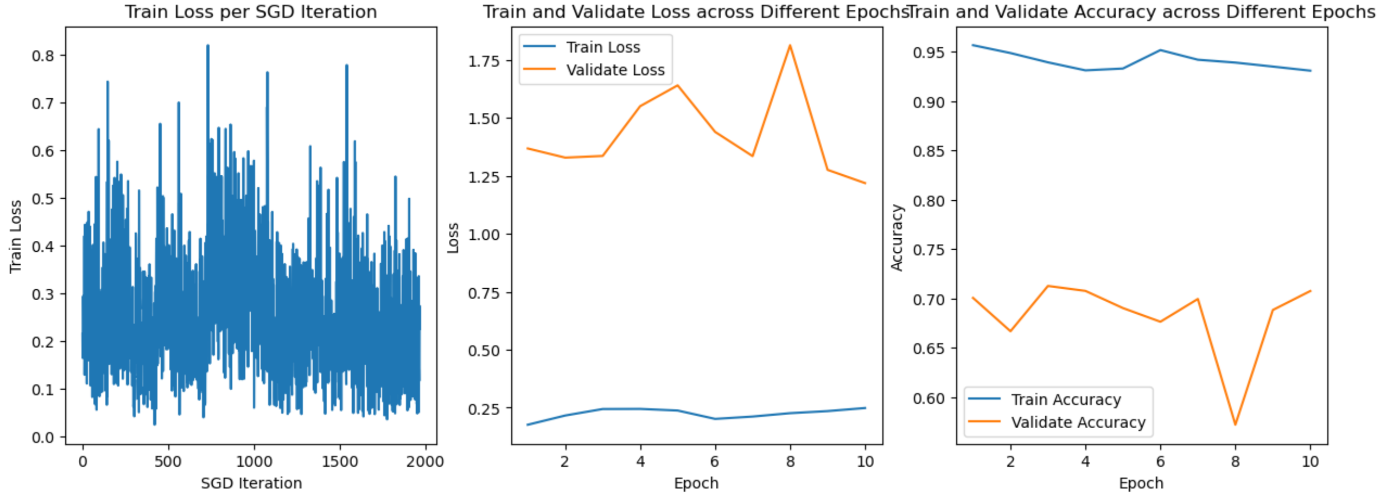
```
Epoch=0,train_loss=0.1759623885154724,validate_loss=1.3685113191604614
Train_accuracy=95.65%,validate_accuracy=70.05%
Current epoch is best so far, saving model...
Epoch=1,train_loss=0.2158375233411789,validate_loss=1.3289837837219238
Train_accuracy=94.85%,validate_accuracy=66.67%
Epoch=2,train_loss=0.24386034905910492,validate_loss=1.3362921476364136
Train_accuracy=93.91%,validate_accuracy=71.26%
Current epoch is best so far, saving model...
Epoch=3,train_loss=0.2443723976612091,validate_loss=1.551171898841858
Train_accuracy=93.1%,validate_accuracy=70.75%
Epoch=4,train_loss=0.23730111122131348,validate_loss=1.6409270763397217
Train_accuracy=93.28%,validate_accuracy=69.01%
Epoch=5,train_loss=0.2012268602848053,validate_loss=1.4399733543395996
Train_accuracy=95.15%,validate_accuracy=67.63%
Epoch=6,train_loss=0.21134880185127258,validate_loss=1.335500955581665
Train_accuracy=94.17%,validate_accuracy=69.94%
Epoch=7,train_loss=0.2258778214454651,validate_loss=1.8142789602279663
Train_accuracy=93.89%,validate_accuracy=57.19%
Epoch=8,train_loss=0.23486410081386566,validate_loss=1.2762583494186401
Train_accuracy=93.48%,validate_accuracy=68.82%
Epoch=9,train_loss=0.24815918505191803,validate_loss=1.2190793752670288
Train_accuracy=93.06%,validate_accuracy=70.75%
```

In [9]:

```python
import matplotlib.pyplot as plt
import numpy as np

# Reshape losses and accuracies arrays to match the total number of train iterations
train_loss_per_iteration = np.array(batch_loss).reshape(-1)

# Create the plots
plt.figure(figsize=(15, 5))

# Plot 1: The train loss per SGD iteration
plt.subplot(1, 3, 1)
plt.plot(train_loss_per_iteration)
plt.xlabel('SGD Iteration')
plt.ylabel('Train Loss')
plt.title('Train Loss per SGD Iteration')

# Plot 2: The train and validate loss across different epochs
plt.subplot(1, 3, 2)
plt.plot(np.arange(1, N_epochs+1), losses, label='Train Loss')
plt.plot(np.arange(1, N_epochs+1), validate_losses, label='Validate Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.title('Train and Validate Loss across Different Epochs')
plt.legend()

# Plot 3: The train and validate metric across different epochs
plt.subplot(1, 3, 3)
plt.plot(np.arange(1, N_epochs+1), accuracies, label='Train Accuracy')
plt.plot(np.arange(1, N_epochs+1), validate_accuracies, label='Validate Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.title('Train and Validate Accuracy across Different Epochs')
plt.legend()

plt.tight_layout
```

Out[9]:

```
<function matplotlib.pyplot.tight_layout(*, pad=1.08, h_pad=None, w_pad=None, rect=None)
>
```



Question 4

Note: I have purposely chose hyperparamters before that gives high loss so that I now when i hypertune the model, the convergence,loss and accuracy has stark improvement.

Steps I followed to hypertune:

1. Increased number of epochs - In this step i could see a lot of fluctuations in my metric - accuracy.
2. Increased batch size - In this step I could see that the fluctuations in accuracy were eliminated, but there was still one notcieable jump in accuracy metric.
3. Decreased learning ratio - In this step, i could see that fluctuations in accuracy were eliminated and accuracy curve was relatively smooth.
4. From the above steps I learnt that for the following data, tuning learning ratio improved the accuracy metric the most.
5. To get the final hypertuned parameter, I Increased batch size, decreased learning ratio and kept the number of epochs as same comapred to the hyperparameters we used in Q3.

Note: I'm aware, the validation loss does not decrease, and it is due to the fact that the two data sets we took are vastly different.

However for the assignment purpose, to hypertune and fit my data even more, I increased the batch size, number of epochs and decreased the learning rate.

In [10]:

```python
# hyperparameters
lr = 0.05
batch_size = 64
N_epochs = 25

loss_fun = nn.CrossEntropyLoss()

train_dataloader = DataLoader(train_dataset, batch_size = batch_size, shuffle = True)
validate_dataloader = DataLoader(validate_dataset, batch_size = batch_size, shuffle = Tr

# Adam Optimizer
optimizer = torch.optim.Adam(mymodel.parameters(),lr = lr)

losses = []
accuracies = []

validate_losses = []
```

```
validate_accuracies = []

current_best_accuracy = 0.0

import numpy as np
for epoch in range(N_epochs):

    batch_loss = []
    batch_accuracy = []

    for x_batch,y_batch in train_dataloader:
        prediction_score = mymodel(x_batch)
        loss = loss_fun(prediction_score,y_batch)
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
        batch_loss.append(loss.detach().numpy())
        prediction_label = torch.argmax(prediction_score.detach(),dim=1).numpy()
        batch_accuracy.append(np.sum(prediction_label == y_batch.numpy())/x_batch.shape[

    validate_batch_loss = []
    validate_batch_accuracy = []

    for x_batch,y_batch in validate_dataloader:
        prediction_score = mymodel(x_batch)
        loss = loss_fun(prediction_score,y_batch)
        validate_batch_loss.append(loss.detach())
        prediction_label = torch.argmax(prediction_score.detach(),dim=1).numpy()
        validate_batch_accuracy.append(np.sum(prediction_label == y_batch.numpy())/x_bat

    losses.append(np.mean(np.array(batch_loss)))
    validate_losses.append(np.mean(np.array(validate_batch_loss)))

    accuracies.append(np.mean(np.array(batch_accuracy)))
    validate_accuracies.append(np.mean(np.array(validate_batch_accuracy)))

    print(f"Epoch={epoch},train_loss={losses[-1]},validate_loss={validate_losses[-1]}")
    print(f"Train_accuracy={np.round(accuracies[-1]*100,2)}%,validate_accuracy={np.round



    if validate_accuracies[-1]>current_best_accuracy:
        print("Current epoch is best so far, saving model...")
        torch.save(mymodel.state_dict(),'current_best_model')
        current_best_accuracy = validate_accuracies[-1]
```

```
Epoch=0,train_loss=0.20059753954410553,validate_loss=2.1363370418548584
Train_accuracy=94.95%,validate_accuracy=72.03%
Current epoch is best so far, saving model...
Epoch=1,train_loss=0.1914178431034088,validate_loss=1.431452751159668
Train_accuracy=95.76%,validate_accuracy=72.27%
Current epoch is best so far, saving model...
Epoch=2,train_loss=0.1780841201543808,validate_loss=1.3532395362854004
Train_accuracy=96.46%,validate_accuracy=72.44%
Current epoch is best so far, saving model...
Epoch=3,train_loss=0.1903146207332611,validate_loss=1.3609135150909424
Train_accuracy=95.4%,validate_accuracy=71.11%
Epoch=4,train_loss=0.19908231496810913,validate_loss=1.6711556911468506
Train_accuracy=95.36%,validate_accuracy=70.63%
Epoch=5,train_loss=0.24685172736644745,validate_loss=1.258803367614746
Train_accuracy=93.42%,validate_accuracy=64.42%
Epoch=6,train_loss=0.2543299198150635,validate_loss=1.5087683200836182
Train_accuracy=93.74%,validate_accuracy=61.7%
Epoch=7,train_loss=0.25177663564682007,validate_loss=1.3017669916152954
Train_accuracy=92.45%,validate_accuracy=69.24%
```

```
Epoch=8,train_loss=0.2709752321243286,validate_loss=1.2162368297576904
Train_accuracy=91.63%,validate_accuracy=67.8%
Epoch=9,train_loss=0.26907458901405334,validate_loss=1.309976577758789
Train_accuracy=91.51%,validate_accuracy=70.26%
Epoch=10,train_loss=0.20871196687221527,validate_loss=1.44466233253479
Train_accuracy=94.06%,validate_accuracy=71.32%
Epoch=11,train_loss=0.19350992143154144,validate_loss=1.3507078886032104
Train_accuracy=94.7%,validate_accuracy=70.32%
Epoch=12,train_loss=0.19749745726585388,validate_loss=1.490451455116272
Train_accuracy=94.53%,validate_accuracy=70.16%
Epoch=13,train_loss=0.20402474701404572,validate_loss=1.1915591955184937
Train_accuracy=94.27%,validate_accuracy=70.67%
Epoch=14,train_loss=0.2057374268770218,validate_loss=1.3280588388442993
Train_accuracy=94.26%,validate_accuracy=70.05%
Epoch=15,train_loss=0.20377355813980103,validate_loss=1.4187231063842773
Train_accuracy=94.08%,validate_accuracy=69.81%
Epoch=16,train_loss=0.21508631110191345,validate_loss=1.3903018236160278
Train_accuracy=94.13%,validate_accuracy=69.24%
Epoch=17,train_loss=0.18956200778484344,validate_loss=1.3018887042999268
Train_accuracy=94.85%,validate_accuracy=70.19%
Epoch=18,train_loss=0.19633983075618744,validate_loss=1.5759528875350952
Train_accuracy=95.23%,validate_accuracy=70.27%
Epoch=19,train_loss=0.18859101831912994,validate_loss=1.2344307899475098
Train_accuracy=95.35%,validate_accuracy=70.98%
Epoch=20,train_loss=0.19544222950935364,validate_loss=1.4688223600387573
Train_accuracy=94.71%,validate_accuracy=69.73%
Epoch=21,train_loss=0.31119492650032043,validate_loss=1.4383047819137573
Train_accuracy=90.82%,validate_accuracy=65.88%
Epoch=22,train_loss=0.3301560878753662,validate_loss=1.4577940702438354
Train_accuracy=91.44%,validate_accuracy=65.14%
Epoch=23,train_loss=0.31477051973342896,validate_loss=1.5690879821777344
Train_accuracy=92.36%,validate_accuracy=69.73%
Epoch=24,train_loss=0.30669519305229187,validate_loss=1.584274411201477
Train_accuracy=92.86%,validate_accuracy=69.11%
```

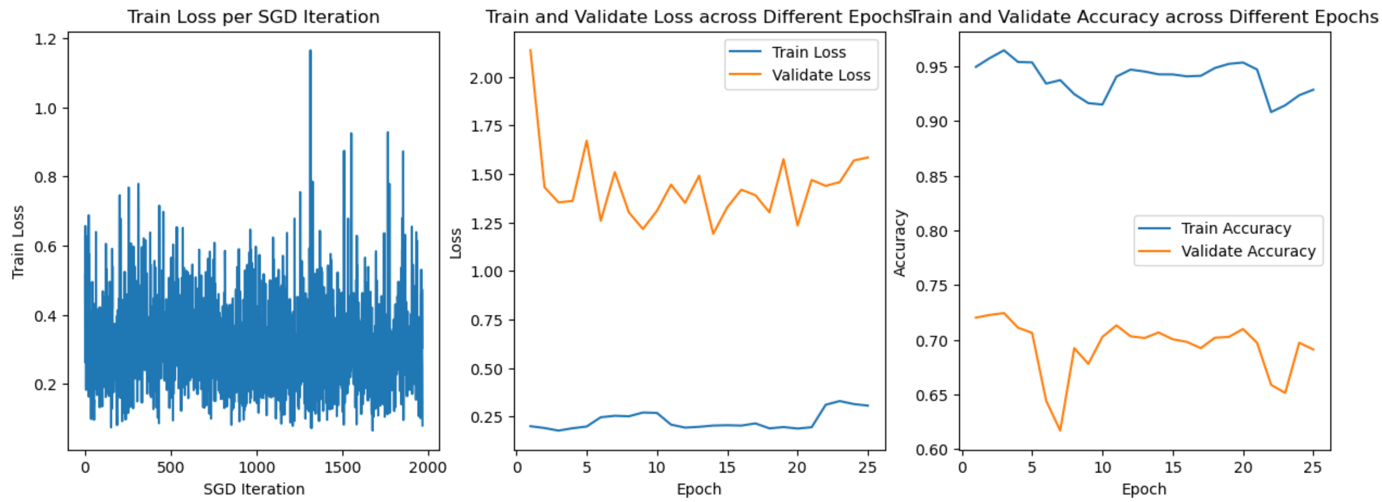
In [11]:

```
import matplotlib.pyplot as plt
import numpy as np

# Reshape losses and accuracies arrays to match the total number of train iterations
train_loss_per_iteration = np.array(batch_loss).reshape(-1)

# Create the plots
plt.figure(figsize=(15, 5))

# Plot 1: The train loss per SGD iteration
plt.subplot(1, 3, 1)
plt.plot(train_loss_per_iteration)
plt.xlabel('SGD Iteration')
plt.ylabel('Train Loss')
plt.title('Train Loss per SGD Iteration')

# Plot 2: The train and validate loss across different epochs
plt.subplot(1, 3, 2)
plt.plot(np.arange(1, N_epochs+1), losses, label='Train Loss')
plt.plot(np.arange(1, N_epochs+1), validate_losses, label='Validate Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.title('Train and Validate Loss across Different Epochs')
plt.legend()

# Plot 3: The train and validate metric across different epochs
plt.subplot(1, 3, 3)
plt.plot(np.arange(1, N_epochs+1), accuracies, label='Train Accuracy')
plt.plot(np.arange(1, N_epochs+1), validate_accuracies, label='Validate Accuracy')
plt.xlabel('Epoch')
```

```
plt.ylabel('Accuracy')
plt.title('Train and Validate Accuracy across Different Epochs')
plt.legend()

plt.tight_layout
```

Out[11]:

```
<function matplotlib.pyplot.tight_layout(*, pad=1.08, h_pad=None, w_pad=None, rect=None)
>
```



In [12]:

```
# hyperparameters
lr = 0.05
batch_size = 128
N_epochs = 10

loss_fun = nn.CrossEntropyLoss()

train_dataloader = DataLoader(train_dataset, batch_size = batch_size, shuffle = True)
validate_dataloader = DataLoader(validate_dataset, batch_size = batch_size, shuffle = Tr

# Adam Optimizer
optimizer = torch.optim.Adam(mymodel.parameters(),lr = lr)

losses = []
accuracies = []

validate_losses = []
validate_accuracies = []

current_best_accuracy = 0.0

import numpy as np
for epoch in range(N_epochs):

    batch_loss = []
    batch_accuracy = []

    for x_batch,y_batch in train_dataloader:
        prediction_score = mymodel(x_batch)
        loss = loss_fun(prediction_score,y_batch)
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
        batch_loss.append(loss.detach().numpy())
        prediction_label = torch.argmax(prediction_score.detach(),dim=1).numpy()
        batch_accuracy.append(np.sum(prediction_label == y_batch.numpy())/x_batch.shape[

    validate_batch_loss = []
    validate_batch_accuracy = []

    for x_batch,y_batch in validate_dataloader:
```

```
            prediction_score = mymodel(x_batch)
            loss = loss_fun(prediction_score,y_batch)
            validate_batch_loss.append(loss.detach())
            prediction_label = torch.argmax(prediction_score.detach(),dim=1).numpy()
            validate_batch_accuracy.append(np.sum(prediction_label == y_batch.numpy())/x_bat

    losses.append(np.mean(np.array(batch_loss)))
    validate_losses.append(np.mean(np.array(validate_batch_loss)))

    accuracies.append(np.mean(np.array(batch_accuracy)))
    validate_accuracies.append(np.mean(np.array(validate_batch_accuracy)))

    print(f"Epoch={epoch},train_loss={losses[-1]},validate_loss={validate_losses[-1]}")
    print(f"Train_accuracy={np.round(accuracies[-1]*100,2)}%,validate_accuracy={np.round




    if validate_accuracies[-1]>current_best_accuracy:
        print("Current epoch is best so far, saving model...")
        torch.save(mymodel.state_dict(),'current_best_model')
        current_best_accuracy = validate_accuracies[-1]
```

```
Epoch=0,train_loss=0.2910799980163574,validate_loss=1.3877204656600952
Train_accuracy=93.29%,validate_accuracy=70.57%
Current epoch is best so far, saving model...
Epoch=1,train_loss=0.2885233461856842,validate_loss=1.3361672163009644
Train_accuracy=93.29%,validate_accuracy=70.35%
Epoch=2,train_loss=0.2951803803443908,validate_loss=1.4966228008270264
Train_accuracy=93.39%,validate_accuracy=70.6%
Current epoch is best so far, saving model...
Epoch=3,train_loss=0.2995074987411499,validate_loss=1.3447386026382446
Train_accuracy=93.13%,validate_accuracy=69.45%
Epoch=4,train_loss=0.30262491106987,validate_loss=1.558706521987915
Train_accuracy=93.25%,validate_accuracy=71.4%
Current epoch is best so far, saving model...
Epoch=5,train_loss=0.2863333225250244,validate_loss=1.5161794424057007
Train_accuracy=93.7%,validate_accuracy=70.51%
Epoch=6,train_loss=0.29376354813575745,validate_loss=1.3480241298675537
Train_accuracy=93.25%,validate_accuracy=69.51%
Epoch=7,train_loss=0.293213427066803,validate_loss=1.5917545557022095
Train_accuracy=93.22%,validate_accuracy=69.63%
Epoch=8,train_loss=0.2834555208683014,validate_loss=1.6249926090240479
Train_accuracy=93.53%,validate_accuracy=69.63%
Epoch=9,train_loss=0.2790558934211731,validate_loss=1.7881008386611938
Train_accuracy=93.79%,validate_accuracy=69.15%
```

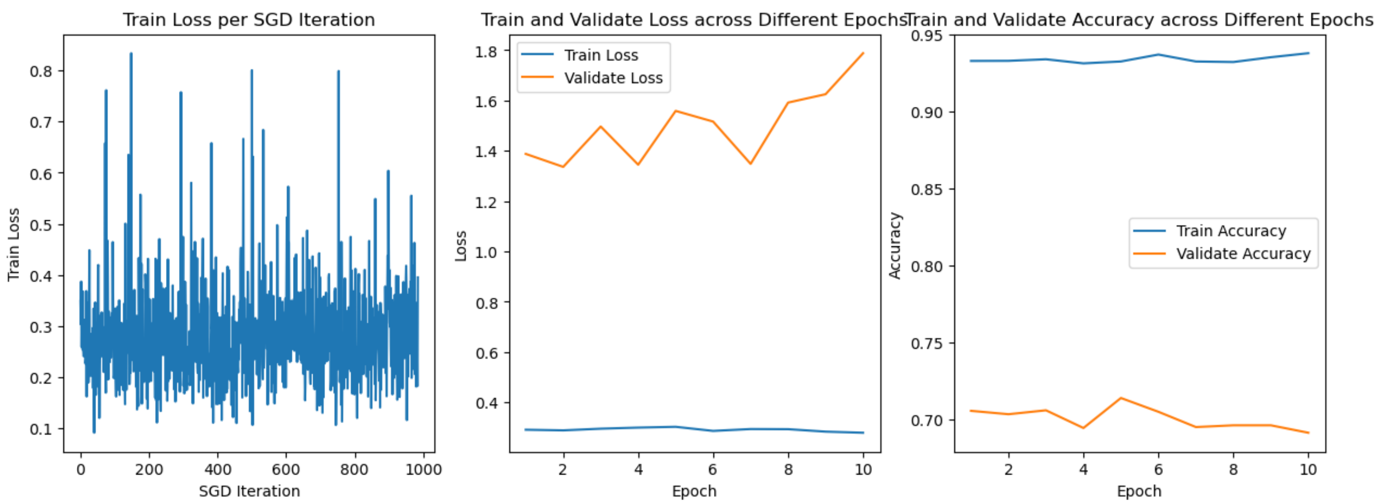
In [13]:

```
import matplotlib.pyplot as plt
import numpy as np

# Reshape losses and accuracies arrays to match the total number of train iterations
train_loss_per_iteration = np.array(batch_loss).reshape(-1)

# Create the plots
plt.figure(figsize=(15, 5))

# Plot 1: The train loss per SGD iteration
plt.subplot(1, 3, 1)
plt.plot(train_loss_per_iteration)
plt.xlabel('SGD Iteration')
plt.ylabel('Train Loss')
plt.title('Train Loss per SGD Iteration')

# Plot 2: The train and validate loss across different epochs
plt.subplot(1, 3, 2)
plt.plot(np.arange(1, N_epochs+1), losses, label='Train Loss')
```

```
plt.plot(np.arange(1, N_epochs+1), validate_losses, label='Validate Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.title('Train and Validate Loss across Different Epochs')
plt.legend()

# Plot 3: The train and validate metric across different epochs
plt.subplot(1, 3, 3)
plt.plot(np.arange(1, N_epochs+1), accuracies, label='Train Accuracy')
plt.plot(np.arange(1, N_epochs+1), validate_accuracies, label='Validate Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.title('Train and Validate Accuracy across Different Epochs')
plt.legend()

plt.tight_layout
```

Out[13]:

```
<function matplotlib.pyplot.tight_layout(*, pad=1.08, h_pad=None, w_pad=None, rect=None)
>
```



In [14]:

```
# hyperparameters
lr = 0.004
batch_size = 64
N_epochs = 10

loss_fun = nn.CrossEntropyLoss()

train_dataloader = DataLoader(train_dataset, batch_size = batch_size, shuffle = True)
validate_dataloader = DataLoader(validate_dataset, batch_size = batch_size, shuffle = Tr

# Adam Optimizer
optimizer = torch.optim.Adam(mymodel.parameters(),lr = lr)

losses = []
accuracies = []

validate_losses = []
validate_accuracies = []

current_best_accuracy = 0.0

import numpy as np
for epoch in range(N_epochs):

    batch_loss = []
    batch_accuracy = []

    for x_batch,y_batch in train_dataloader:
        prediction_score = mymodel(x_batch)
        loss = loss_fun(prediction_score,y_batch)
```

```
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
        batch_loss.append(loss.detach().numpy())
        prediction_label = torch.argmax(prediction_score.detach(),dim=1).numpy()
        batch_accuracy.append(np.sum(prediction_label == y_batch.numpy())/x_batch.shape[

    validate_batch_loss = []
    validate_batch_accuracy = []

    for x_batch,y_batch in validate_dataloader:
        prediction_score = mymodel(x_batch)
        loss = loss_fun(prediction_score,y_batch)
        validate_batch_loss.append(loss.detach())
        prediction_label = torch.argmax(prediction_score.detach(),dim=1).numpy()
        validate_batch_accuracy.append(np.sum(prediction_label == y_batch.numpy())/x_bat

    losses.append(np.mean(np.array(batch_loss)))
    validate_losses.append(np.mean(np.array(validate_batch_loss)))

    accuracies.append(np.mean(np.array(batch_accuracy)))
    validate_accuracies.append(np.mean(np.array(validate_batch_accuracy)))

    print(f"Epoch={epoch},train_loss={losses[-1]},validate_loss={validate_losses[-1]}")
    print(f"Train_accuracy={np.round(accuracies[-1]*100,2)}%,validate_accuracy={np.round




    if validate_accuracies[-1]>current_best_accuracy:
        print("Current epoch is best so far, saving model...")
        torch.save(mymodel.state_dict(),'current_best_model')
        current_best_accuracy = validate_accuracies[-1]
```

```
Epoch=0,train_loss=0.27251654863357544,validate_loss=1.7364015579223633
Train_accuracy=93.93%,validate_accuracy=69.32%
Current epoch is best so far, saving model...
Epoch=1,train_loss=0.27061983942985535,validate_loss=1.7642725706100464
Train_accuracy=93.99%,validate_accuracy=69.7%
Current epoch is best so far, saving model...
Epoch=2,train_loss=0.2697236239910126,validate_loss=1.750284194946289
Train_accuracy=94.06%,validate_accuracy=69.92%
Current epoch is best so far, saving model...
Epoch=3,train_loss=0.26899194717407227,validate_loss=1.7135013341903687
Train_accuracy=94.11%,validate_accuracy=70.04%
Current epoch is best so far, saving model...
Epoch=4,train_loss=0.26821571588516235,validate_loss=1.754568338394165
Train_accuracy=94.13%,validate_accuracy=70.04%
Epoch=5,train_loss=0.2683529555797577,validate_loss=1.7138054370880127
Train_accuracy=94.18%,validate_accuracy=70.6%
Current epoch is best so far, saving model...
Epoch=6,train_loss=0.2658140957355499,validate_loss=1.7355494499206543
Train_accuracy=94.04%,validate_accuracy=70.37%
Epoch=7,train_loss=0.2636089622974396,validate_loss=1.7453280687332153
Train_accuracy=94.1%,validate_accuracy=70.56%
Epoch=8,train_loss=0.26164013147354126,validate_loss=1.6501615047454834
Train_accuracy=94.1%,validate_accuracy=70.38%
Epoch=9,train_loss=0.259357213973999,validate_loss=1.9072538614273071
Train_accuracy=94.28%,validate_accuracy=70.68%
Current epoch is best so far, saving model...
```

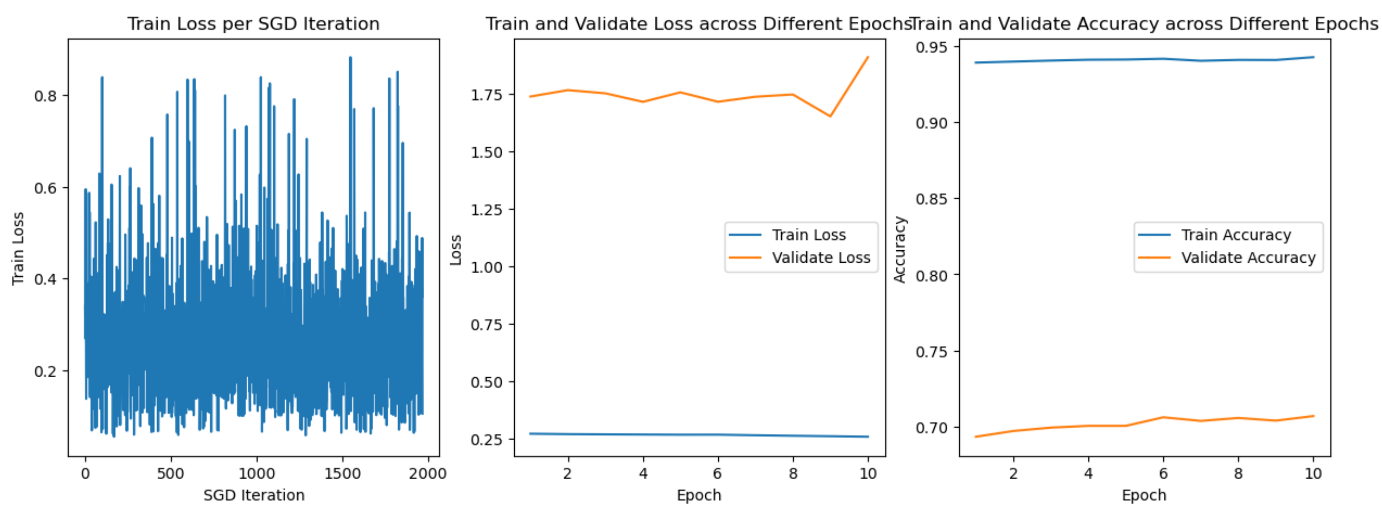
In [15]:

```
import matplotlib.pyplot as plt
import numpy as np

# Reshape losses and accuracies arrays to match the total number of train iterations
train_loss_per_iteration = np.array(batch_loss).reshape(-1)
```

```python
# Create the plots
plt.figure(figsize=(15, 5))

# Plot 1: The train loss per SGD iteration
plt.subplot(1, 3, 1)
plt.plot(train_loss_per_iteration)
plt.xlabel('SGD Iteration')
plt.ylabel('Train Loss')
plt.title('Train Loss per SGD Iteration')

# Plot 2: The train and validate loss across different epochs
plt.subplot(1, 3, 2)
plt.plot(np.arange(1, N_epochs+1), losses, label='Train Loss')
plt.plot(np.arange(1, N_epochs+1), validate_losses, label='Validate Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.title('Train and Validate Loss across Different Epochs')
plt.legend()

# Plot 3: The train and validate metric across different epochs
plt.subplot(1, 3, 3)
plt.plot(np.arange(1, N_epochs+1), accuracies, label='Train Accuracy')
plt.plot(np.arange(1, N_epochs+1), validate_accuracies, label='Validate Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.title('Train and Validate Accuracy across Different Epochs')
plt.legend()

plt.tight_layout
```

Out[15]:

```
<function matplotlib.pyplot.tight_layout(*, pad=1.08, h_pad=None, w_pad=None, rect=None)
>
```



In [16]:

```python
# hyperparameters
lr = 0.004
batch_size = 128
N_epochs = 10

loss_fun = nn.CrossEntropyLoss()

train_dataloader = DataLoader(train_dataset, batch_size = batch_size, shuffle = True)
validate_dataloader = DataLoader(validate_dataset, batch_size = batch_size, shuffle = Tr

# Adam Optimizer
optimizer = torch.optim.Adam(mymodel.parameters(),lr = lr)

losses = []
accuracies = []
```

```
validate_losses = []
validate_accuracies = []

current_best_accuracy = 0.0

import numpy as np
for epoch in range(N_epochs):

    batch_loss = []
    batch_accuracy = []

    for x_batch,y_batch in train_dataloader:
        prediction_score = mymodel(x_batch)
        loss = loss_fun(prediction_score,y_batch)
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
        batch_loss.append(loss.detach().numpy())
        prediction_label = torch.argmax(prediction_score.detach(),dim=1).numpy()
        batch_accuracy.append(np.sum(prediction_label == y_batch.numpy())/x_batch.shape[

    validate_batch_loss = []
    validate_batch_accuracy = []

    for x_batch,y_batch in validate_dataloader:
        prediction_score = mymodel(x_batch)
        loss = loss_fun(prediction_score,y_batch)
        validate_batch_loss.append(loss.detach())
        prediction_label = torch.argmax(prediction_score.detach(),dim=1).numpy()
        validate_batch_accuracy.append(np.sum(prediction_label == y_batch.numpy())/x_bat

    losses.append(np.mean(np.array(batch_loss)))
    validate_losses.append(np.mean(np.array(validate_batch_loss)))

    accuracies.append(np.mean(np.array(batch_accuracy)))
    validate_accuracies.append(np.mean(np.array(validate_batch_accuracy)))

    print(f"Epoch={epoch},train_loss={losses[-1]},validate_loss={validate_losses[-1]}")
    print(f"Train_accuracy={np.round(accuracies[-1]*100,2)}%,validate_accuracy={np.round



    if validate_accuracies[-1]>current_best_accuracy:
        print("Current epoch is best so far, saving model...")
        torch.save(mymodel.state_dict(),'current_best_model')
        current_best_accuracy = validate_accuracies[-1]
```

```
Epoch=0,train_loss=0.2561247944831848,validate_loss=1.9544044733047485
Train_accuracy=94.42%,validate_accuracy=70.45%
Current epoch is best so far, saving model...
Epoch=1,train_loss=0.256153404712677,validate_loss=1.8697177171707153
Train_accuracy=94.48%,validate_accuracy=70.79%
Current epoch is best so far, saving model...
Epoch=2,train_loss=0.2590375244617462,validate_loss=1.8650269508361816
Train_accuracy=94.42%,validate_accuracy=70.65%
Epoch=3,train_loss=0.25350040197372437,validate_loss=1.9021462202072144
Train_accuracy=94.55%,validate_accuracy=70.65%
Epoch=4,train_loss=0.2543175518512726,validate_loss=1.893886923789978
Train_accuracy=94.51%,validate_accuracy=70.47%
Epoch=5,train_loss=0.2550358772277832,validate_loss=1.9063626527786255
Train_accuracy=94.49%,validate_accuracy=70.43%
Epoch=6,train_loss=0.2574337124824524,validate_loss=1.849932074546814
Train_accuracy=94.47%,validate_accuracy=70.82%
Current epoch is best so far, saving model...
Epoch=7,train_loss=0.25794756412506104,validate_loss=1.5478230714797974
```

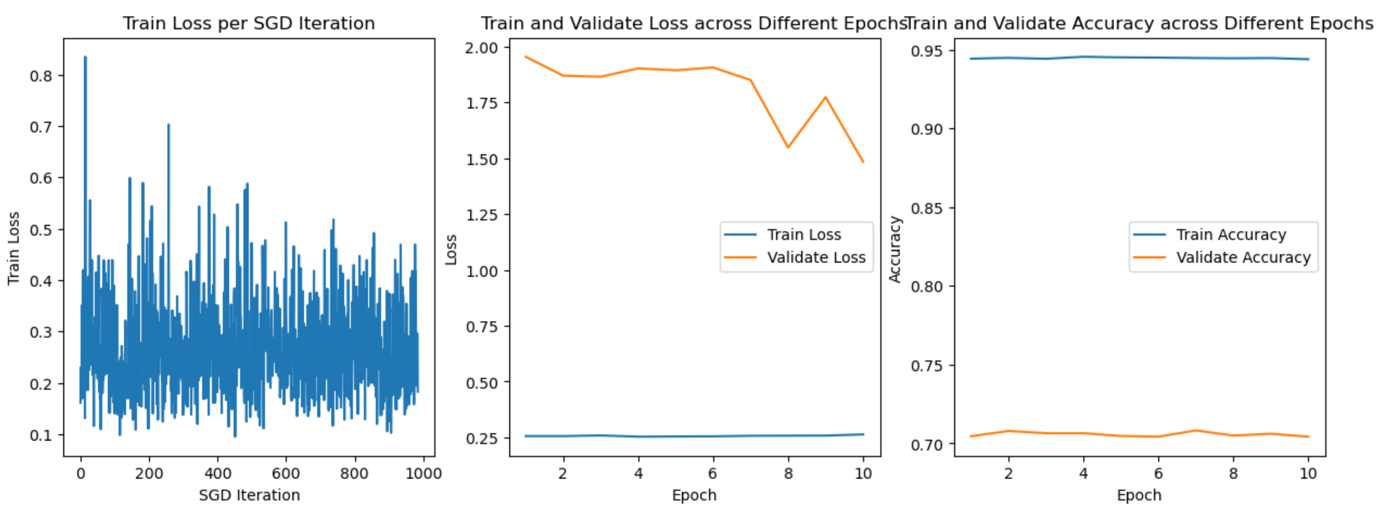
```
Train_accuracy=94.45%,validate_accuracy=70.5%
Epoch=8,train_loss=0.2583456337451935,validate_loss=1.7733960151672363
Train_accuracy=94.46%,validate_accuracy=70.61%
Epoch=9,train_loss=0.26358091831207275,validate_loss=1.4848041534423828
Train_accuracy=94.39%,validate_accuracy=70.43%
```

In [17]:

```python
import matplotlib.pyplot as plt
import numpy as np

# Reshape losses and accuracies arrays to match the total number of train iterations
train_loss_per_iteration = np.array(batch_loss).reshape(-1)

# Create the plots
plt.figure(figsize=(15, 5))

# Plot 1: The train loss per SGD iteration
plt.subplot(1, 3, 1)
plt.plot(train_loss_per_iteration)
plt.xlabel('SGD Iteration')
plt.ylabel('Train Loss')
plt.title('Train Loss per SGD Iteration')

# Plot 2: The train and validate loss across different epochs
plt.subplot(1, 3, 2)
plt.plot(np.arange(1, N_epochs+1), losses, label='Train Loss')
plt.plot(np.arange(1, N_epochs+1), validate_losses, label='Validate Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.title('Train and Validate Loss across Different Epochs')
plt.legend()

# Plot 3: The train and validate metric across different epochs
plt.subplot(1, 3, 3)
plt.plot(np.arange(1, N_epochs+1), accuracies, label='Train Accuracy')
plt.plot(np.arange(1, N_epochs+1), validate_accuracies, label='Validate Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.title('Train and Validate Accuracy across Different Epochs')
plt.legend()

plt.tight_layout
```

Out[17]:

```
<function matplotlib.pyplot.tight_layout(*, pad=1.08, h_pad=None, w_pad=None, rect=None)
>
```



Question 5 (Note: Metric chosen = accuracy)

In [18]:

```python
# Load the best model
mybestmodel = myMultilayerPerceptron(x_train.shape[1],5)
```

```
mybestmodel.load_state_dict(torch.load("current_best_model"))

test_dataloader = DataLoader(test_dataset, batch_size = batch_size, shuffle = True)
test_batch_accuracy = []

for x_batch, y_batch in test_dataloader:
    prediction_score = mybestmodel(x_batch)
    prediction_label = torch.argmax(prediction_score.detach(),dim=1).numpy()
    test_batch_accuracy.append(np.sum(prediction_label == y_batch.numpy())/x_batch.shape

test_accuracy = np.mean(np.array(validate_batch_accuracy))

print(f"Test accuracy = {np.round(test_accuracy*100,2)}%")
```

```
Test accuracy = 70.43%
```

In [ ]:

In [ ]:

In [ ]: