Minor Project Report

on

“SIGN LANGUAGE RECOGNITION USING DEEP LEARNING”

Submitted By

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LIST OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

One of the most difficult tasks in a communication medium is sharing a conversation between a disabled person and a non-disabled person because a deaf-dumb person can practice hand gesture language in their community but not with others. Around 20% of the world's population is deaf-blind, according to research.

This paper presents an in-depth exploration of deep learning-based sign language recognition systems for static images, emphasizing the importance and necessity of such systems. Sign language recognition systems utilizing deep learning techniques have gained significant attention due to their potential to bridge the communication gap between individuals with hearing impairments who use sign language and those who do not understand it.

The difficulty hearing-impaired people have in effectively communicating with the broader public leads to the need for sign language recognition devices. As a visual and gestural language, sign language uses hand gestures, face expressions, and body postures to express meaning. But many people lack the abilities to understand or interpret sign language, which creates impediments to efficient communication.

The creation of reliable and precise sign language recognition systems can give hearing-impaired people a way to express themselves and improve communication. These technologies make it possible for sign language gestures to be automatically translated into text or speech, enabling communication between those with hearing loss and those who do not understand sign language.

Deep learning techniques, particularly convolutional neural networks (CNNs), have exhibited considerable potential in capturing intricate visual patterns and extracting meaningful features from images. By harnessing the power of deep learning, sign language recognition systems can accurately identify and interpret the nuanced details and variations inherent in sign language gestures captured in static images. Deep learning models can automatically learn hierarchical representations from raw input data, enabling them to capture intricate patterns and features that characterize different sign language gestures.

The development of sign language recognition systems is not only crucial for facilitating day-to-day communication but also holds immense significance in education, employment, and social integration. Access to sign language interpretation can enhance the learning experience of individuals with hearing impairments in educational settings, enabling their full participation in classroom activities. In the workplace, sign language recognition systems can empower individuals with hearing impairments by facilitating effective communication with colleagues, clients, and customers.

Moreover, sign language recognition systems contribute to the creation of a more inclusive and accessible society. By enabling communication between individuals with hearing impairments and those who do not comprehend sign language, these systems help dismantle communication barriers, alleviate social isolation, and foster equal opportunities for individuals with hearing impairments across various aspects of life.

In conclusion, the development of deep learning-based sign language recognition systems for static images is critical in addressing the communication challenges faced by individuals with hearing impairments. These systems play a pivotal role in facilitating effective communication, promoting inclusivity, and empowering individuals with hearing impairments in educational, professional, and social contexts.

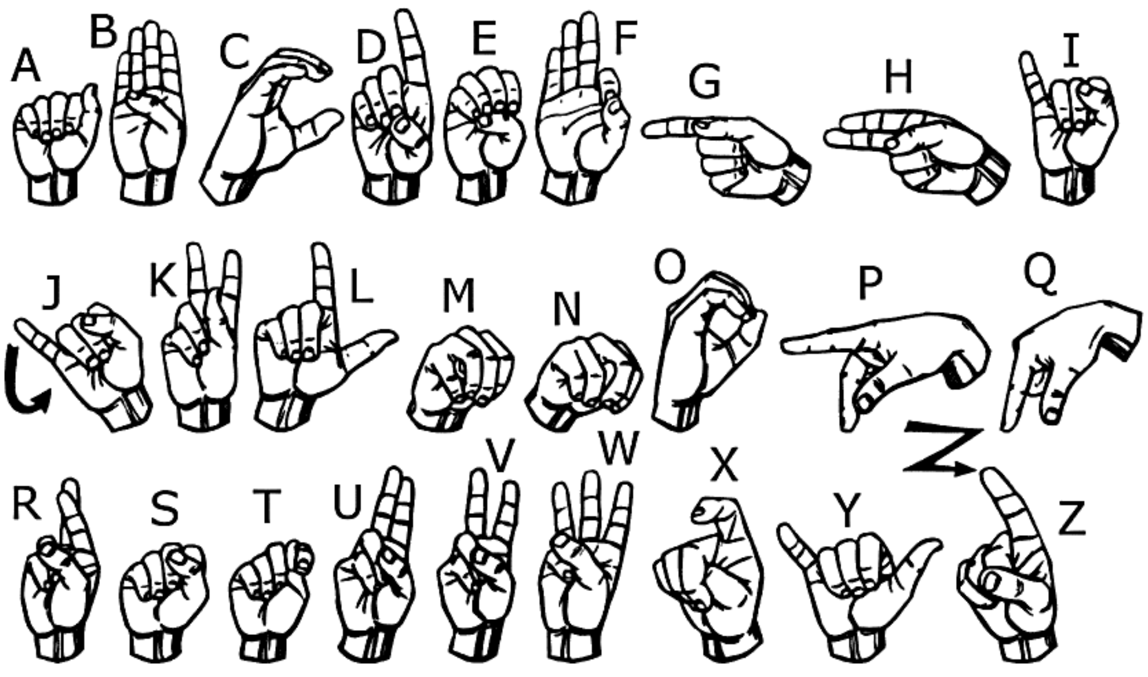


Figure 1: American Sign Language

1. INTRODUCTION

Computers perceive images through pixels, which are the fundamental units of programmable color on a computer display or in an image. Convolution is a mathematical operation that combines signals to identify patterns in images. It involves multiplying arrays of numbers, such as pixels, with a filter matrix or 'kernel' to produce a new array of numbers.

In this undertaking, convolution is applied by duplicating a pixel lattice with a piece and summarizing the increase values. The cycle is rehashed for every pixel, sliding the convolution over the picture.

To implement the convolutional neural network (CNN) for this project, we will utilize the Sequential model from Keras. The Sequential model allows building the network layer by layer using the add() function. The model can be trained using the fit() function, which requires parameters such as training data, test data, validation data, and the number of epochs.

The dataset is taken from Kaggle (https://www.kaggle.com/datasets/datamunge/sign-language-mnist?select=amer_sign2.png).

This dataset contains:

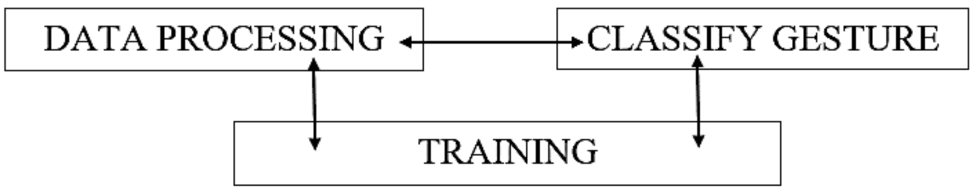


Figure 2: Basic Block Diagram

The dataset is taken from Kaggle: Sign Language MNIST
Input: A greyscale ASL letter image of shape 28X28
Output: Equivalent letter in English alphabet corresponding to the input image.

Note:

No cases for letters J and Z as they require motion.

All the images contain 784 pixels where the values range from 0 to 255.

Labels are numerically encoded from 0 to 25 for A to Z.

In this paper, accuracy is used as the evaluation metric. Accuracy is the ration of correctly classified samples to total number of samples.

Modelling of the CNN:

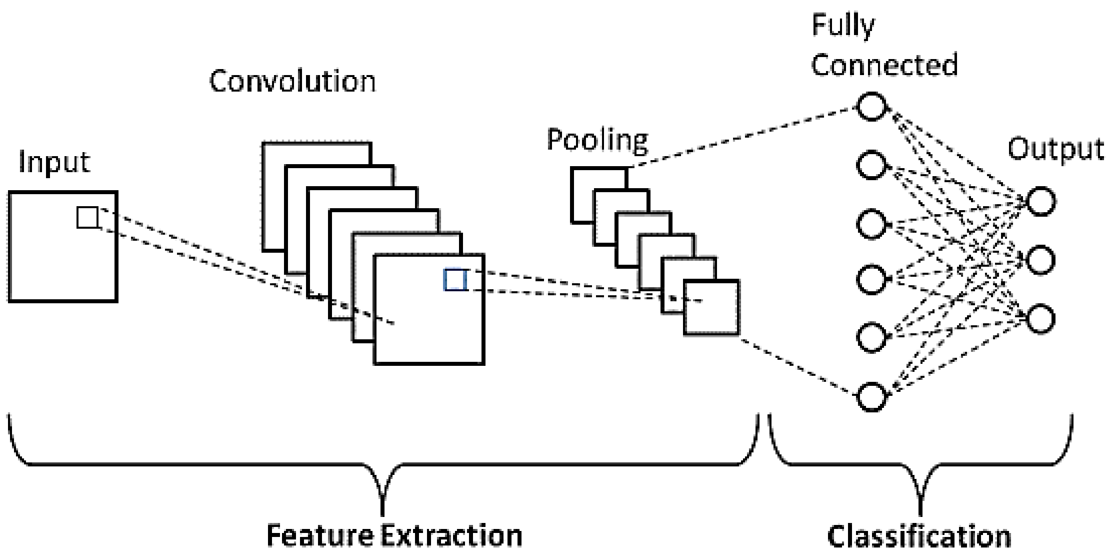


Figure 3: Basic CNN Architecture

1.1. GENERAL OVERVIEW

Due to the language barrier, people with hearing impairments face significant challenges in a world where effective communication is essential in personal, educational, and professional settings. The deaf and hard-of-hearing community relies heavily on sign language for communication, which presents unique challenges for those who are unfamiliar with its intricacies. The issue at hand is the creation of a robust sign language recognition system because of the significance of closing this communication gap.

In order to facilitate seamless communication between sign language users and non-sign language users, this study focuses on accurately interpreting and translating sign language gestures into textual representations.

Handling variations in hand shapes, orientations, and positions, as well as dealing with issues related to lighting conditions, backgrounds, and noise interference, are among the difficulties associated with this endeavor. Other difficulties include capturing and interpreting the intricate hand movements that are inherent in sign language.

Deep learning methods, specifically convolutional neural networks (CNNs), are used to deal with these issues. With the goal of training the model to recognize and classify a wide variety of sign language gestures with high accuracy and robustness, CNNs enable the extraction of meaningful spatial and temporal features from the input data.

The creation of an effective and dependable sign language recognition system that enables people with hearing impairments to communicate effectively is the ultimate goal of this research. This research aims to foster inclusivity, improve the quality of life for people with hearing impairments, and promote effective communication in a society without barriers by contributing to the advancement of assistive technologies, educational resources, and communication accessibility for the deaf and hard-of-hearing community.

1.2. LITERATURE SURVEY

Table 1: LITERATURE SURVEY

Sr. No.	Author	Paper and Publication Details	Findings	Relevance To Project
1	Krishna Chowdary, Akhil & Sandeep, Gunna	Sign Language Recognition using Deep CNN May 2022	Shows how a 3DCNN Structure is used for processing, feature learning and classification	Provides various ways to perform feature extraction and image augmentation.
2	Ahmed Sultan, Walied Makram, Mohammed Kayed, Abdelmaged Amin Ali	Sign language identification and recognition: A comparative study. Article in Open Computer Science January 2022	A paper on the different kinds of systems developed for sign language recognition over the years.	Various techniques, along with being able to see which techniques are feasible for usage.
3	Satwik Ram Kodandaram, N Pavan Kumar, Sunil G L	Sign language recognition. Article in Turkish Journal of Computer and Mathematics Education July 2021.	A research paper which defines various steps for building a recognition system	Understanding the basic necessary steps while building a Sign language recognition system.
4	Priyanka C Pankajakshan, Thilagavathi.B	Sign language recognition system. Published in International Journal for Research in Applied Science & Engineering Technology August 2020	A paper building a sign language recognition system using Computer Vision.	Using computer vision techniques for building the system.

1.3. PROBLEM DEFINITION

1.3.1. Limited Communication for Individuals with Hearing Impairments

Individuals with hearing impairments face significant communication challenges due to the lack of understanding and fluency in sign language among the general population. This communication barrier restricts their inclusion in various social, educational, and professional contexts, limiting their opportunities for engagement and independence. The absence of effective communication channels hinders their ability to express themselves, understand others, and fully participate in everyday interactions.

1.3.2. Complexity and Variations in Sign Language

Sign language is a rich and complex form of communication, characterized by diverse hand shapes, movements, orientations, and facial expressions. The variations in sign language across regions, cultures, and individuals add another layer of complexity. Recognizing and interpreting these variations accurately pose significant challenges for sign language recognition systems. The systems need to handle the intricacies of different sign language gestures to ensure accurate translation into spoken or written language.

1.3.3. Accessibility and Availability of Sign Language Interpretation

Existing sign language interpretation services are often limited in accessibility and availability. Individuals with hearing impairments may face difficulties accessing qualified sign language interpreters, especially in remote areas or certain situations such as classrooms, workplaces, or public spaces. The lack of readily available sign language interpretation restricts their ability to communicate effectively, hindering their educational, professional, and social interactions.

1.3.4. Limited Dataset Availability and Variability

Building robust sign language recognition systems requires access to diverse and comprehensive datasets. However, the availability of large-scale, annotated sign language datasets is limited. The scarcity of data inhibits the training and optimization of sign language recognition models, reducing their accuracy and generalization capabilities. Additionally, variations in signing styles, regional variations, and contextual differences further challenge the development of effective sign language recognition systems.

1.4. PROPOSED SOLUTION STRATEGY

Sign language recognition project starts by importing essential libraries like TensorFlow, Keras, Numpy, and Pandas. The MNIST sign language dataset is obtained from Kaggle, consisting of hand gesture images representing alphabets from A to Z (excluding J and Z due to motion requirements). Pre-processing involves normalizing pixel values and splitting the data into training and testing sets.

A deep learning model is designed using the convolutional neural network (CNN) architecture with Keras. The CNN includes convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification. Multiple configurations and layer sizes are explored to optimize the model's performance.

The model is compiled with the appropriate loss function, optimizer, and evaluation metric. It is then trained on the training data using the fit() function, adjusting epochs and batch size as needed. This allows the model to learn patterns and features of different sign language gestures.

The trained model is evaluated on the test set using the evaluate() function, providing metrics such as accuracy for assessment. This step measures the model's effectiveness in recognizing sign language gestures from the MNIST dataset. The trained model can make predictions on new sign language images.

Additionally, the model can be fine-tuned to improve performance. Experimentation with hyperparameters, architecture modifications, and techniques like data augmentation can enhance accuracy and generalization capabilities of the sign language detection system.

The iterative process of designing, training, evaluating, and fine-tuning the model continues until satisfactory results are achieved. This involves testing different model architectures, adjusting hyperparameters, and employing various optimization techniques to enhance the accuracy and robustness of the sign language detection system.

2. DESIGN STRATEGY

2.1. BLOCK DIAGRAM

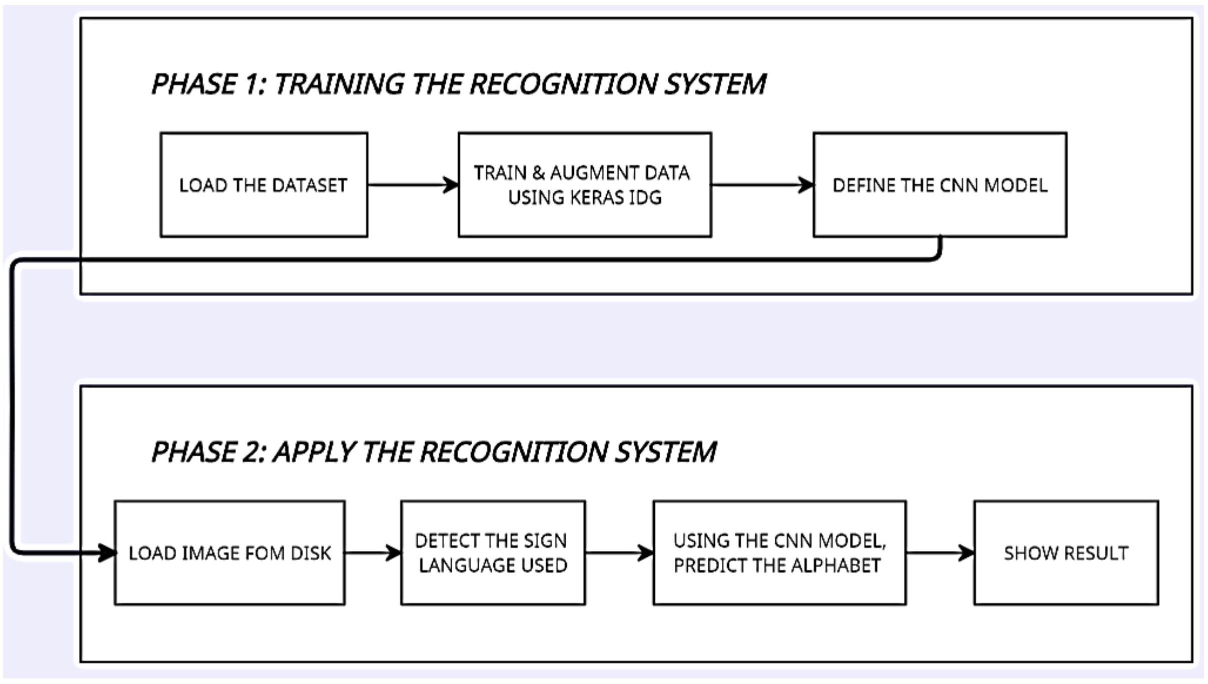

PHASE 1: TRAINING THE RECOGNITION SYSTEM
LOAD THE DATASET
TRAIN & AUGMENT DATA USING KERAS IDG
DEFINE THE CNN MODEL
PHASE 2: APPLY THE RECOGNITION SYSTEM
LOAD IMAGE FOM DISK
DETECT THE SIGN LANGUAGE USED
USING THE CNN MODEL, PREDICT THE ALPHABET
SHOW RESULT

Figure 4: Block Diagram for Training and Testing

Phase 1 is the training of the system which involves loading the necessary libraries along with the dataset, then training the augmented data using the Keras library, and defining the CNN Sequential Model.

Phase 2 involves the loading image, detecting the sign language using the CNN model and showing the result of the same.

2.2. FLOW CHART

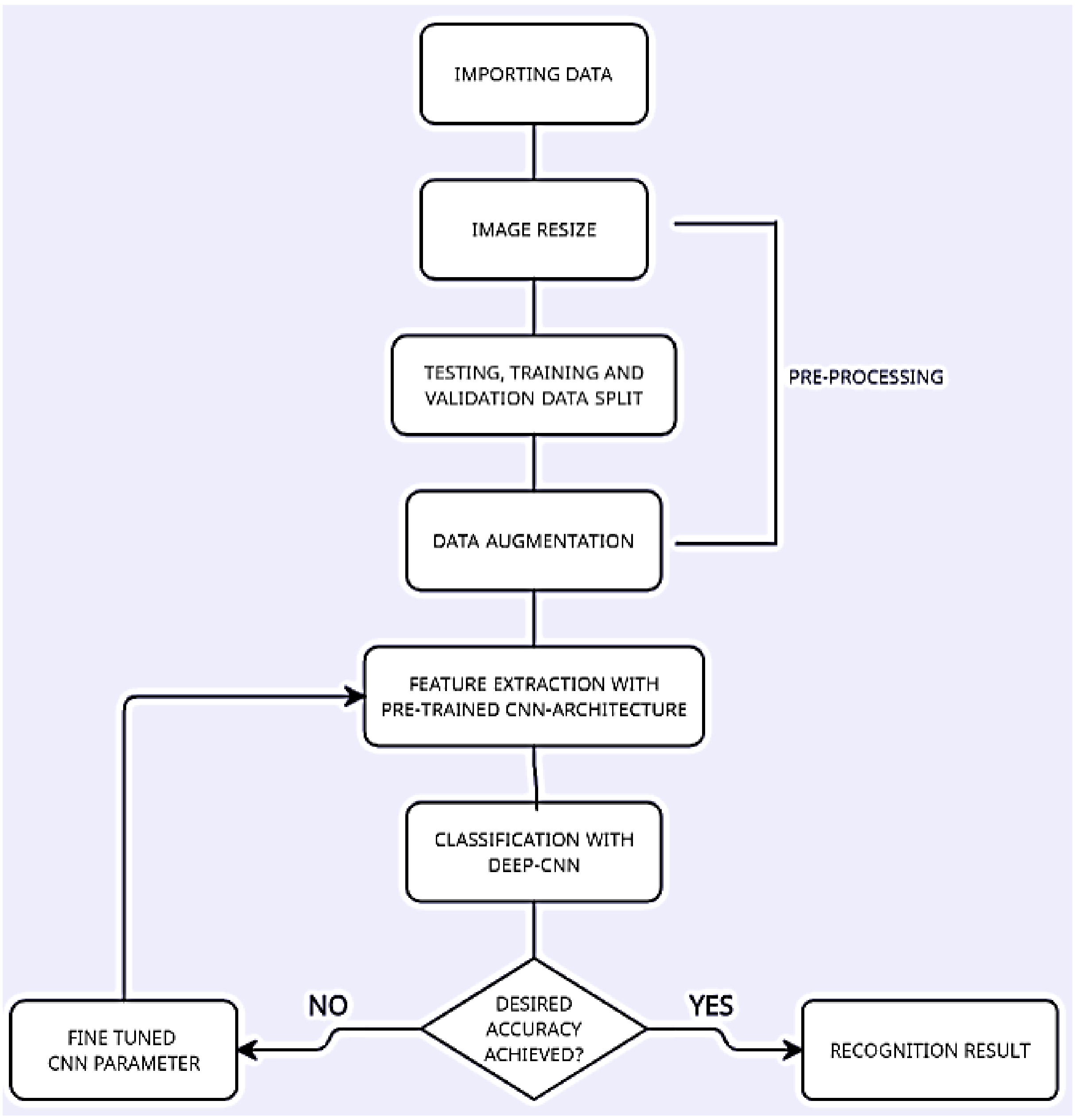

IMPORTING DATA
IMAGE RESIZE
TESTING, TRAINING AND VALIDATION DATA SPLIT
DATA AUGMENTATION
PRE-PROCESSING
FEATURE EXTRACTION WITH PRE-TRAINED CNN-ARCHITECTURE
CLASSIFICATION WITH DEEP-CNN
DESIRED ACCURACY ACHIEVED?
NO
YES
FINE TUNED CNN PARAMETER
RECOGNITION RESULT

Figure 5: Flowchart for Sign Language Recognition System

The given flowchart depicts how the Sign Language System functions.

2.3. MODEL DIAGRAM

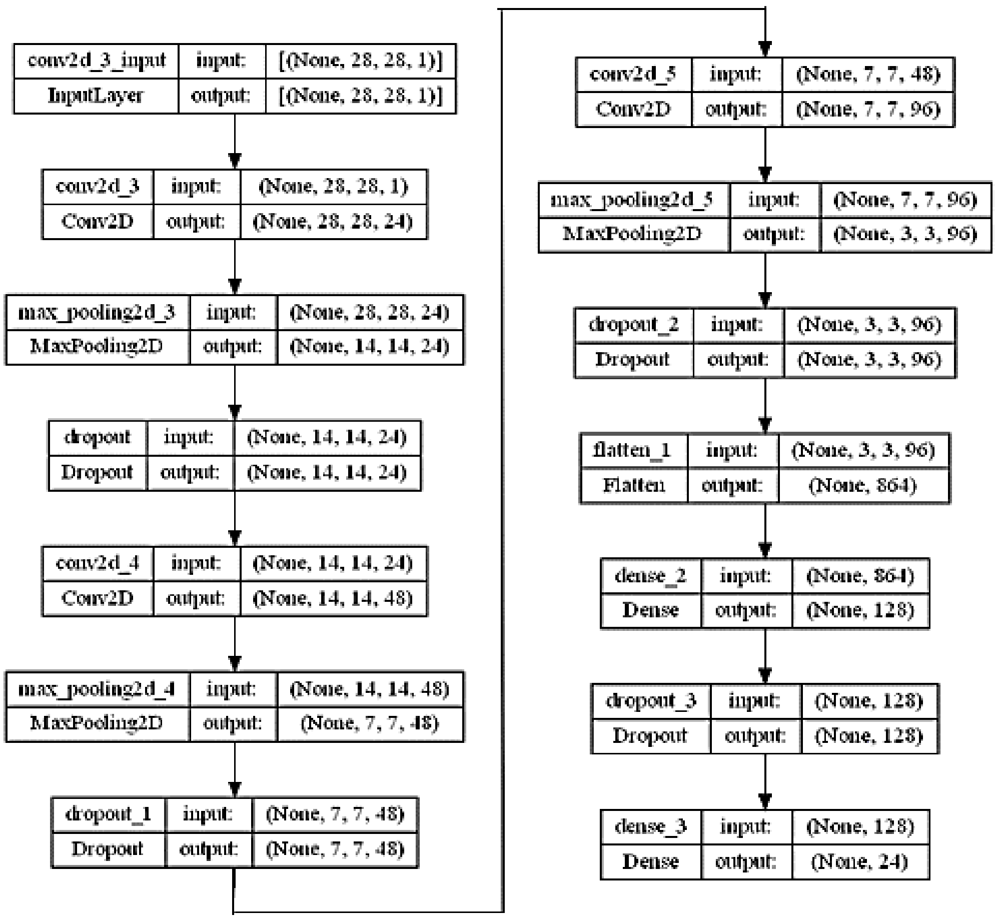
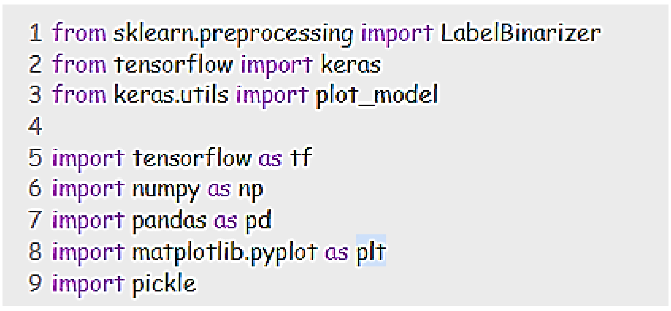

conv2d_3_input | InputLayer | input: [(None, 28, 28, 1)] | output: [(None, 28, 28, 1)]
conv2d_3 | Conv2D | input: (None, 28, 28, 1) | output: (None, 28, 28, 24)
max_pooling2d_3 | MaxPooling2D | input: (None, 28, 28, 24) | output: (None, 14, 14, 24)
dropout | Dropout | input: (None, 14, 14, 24) | output: (None, 14, 14, 24)
conv2d_4 | Conv2D | input: (None, 14, 14, 24) | output: (None, 14, 14, 48)
max_pooling2d_4 | MaxPooling2D | input: (None, 14, 14, 48) | output: (None, 7, 7, 48)
dropout_1 | Dropout | input: (None, 7, 7, 48) | output: (None, 7, 7, 48)
conv2d_5 | Conv2D | input: (None, 7, 7, 48) | output: (None, 7, 7, 96)
max_pooling2d_5 | MaxPooling2D | input: (None, 7, 7, 96) | output: (None, 3, 3, 96)
dropout_2 | Dropout | input: (None, 3, 3, 96) | output: (None, 3, 3, 96)
flatten_1 | Flatten | input: (None, 3, 3, 96) | output: (None, 864)
dense_2 | Dense | input: (None, 864) | output: (None, 128)
dropout_3 | Dropout | input: (None, 128) | output: (None, 128)
dense_3 | Dense | input: (None, 128) | output: (None, 24)

Figure 6: Model Diagram for Sign Language Recognition System

After performing hyperparameter tuning, it is found that the best model for sign language recognition is the model depicted in Figure 6.

3. IMPLEMENTATION DETAILS

1. Import necessary libraries.

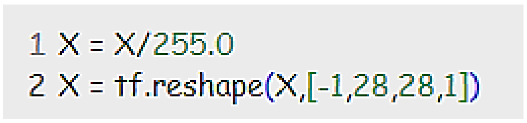


```python
from sklearn.preprocessing import LabelBinarizer
from tensorflow import keras
from keras.utils import plot_model

import tensorflow as tf
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import pickle
```

Figure 7: Code Snippet 1

2. Perform normalization and batching.

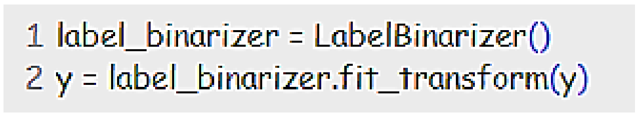
   When gradient decent is used the data converges faster when the data is normalized. Grouping training data into batched decreases the time required to train the model.



```python
X = X/255.0
X = tf.reshape(X,[-1,28,28,1])
```

Figure 8: Code Snippet 2

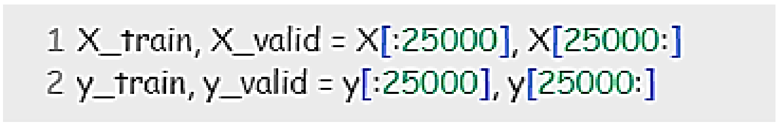
3. Binarize the labels using the scikit-learn library in a one-vs-all fashion and return the one-hot encoded vectors.



```python
label_binarizer = LabelBinarizer()
y = label_binarizer.fit_transform(y)
```

Figure 9: Code Snippet 3

4. Separate the validation data as it helps choosing the best model.

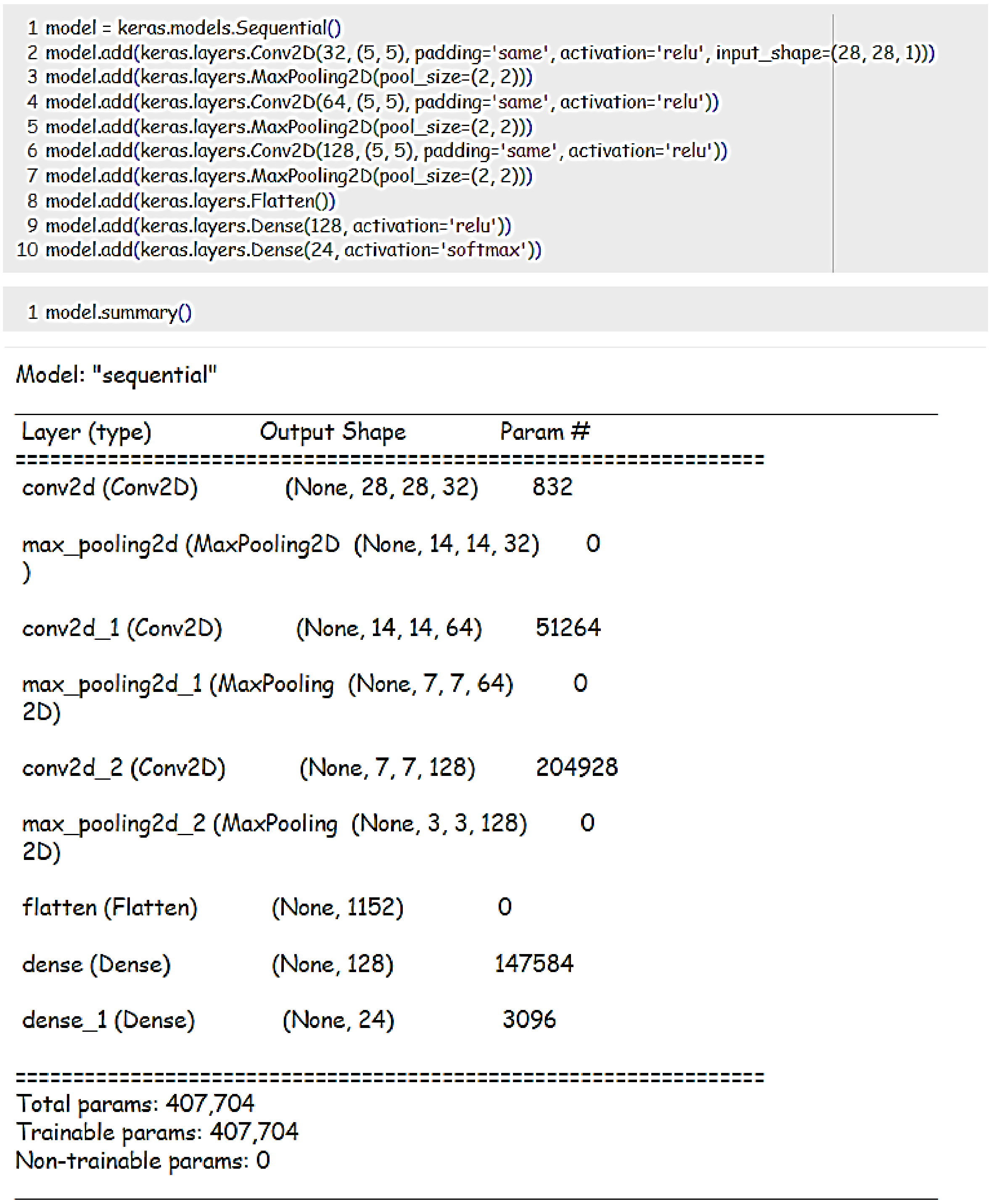


```python
X_train, X_valid = X[:25000], X[25000:]
y_train, y_valid = y[:25000], y[25000:]
```

Figure 10: Code Snippet 4

5. Build a Sequential CNN model using Keras consisting of 3 convolutional layers, 3 max-pooling layers, 1 flatten layer and 2 dense layers.
   - Convolutional Layers:
     - Conv2D layer with 32 filters: 1 instance
     - Conv2D layer with 64 filters: 1 instance

    - Conv2D layer with 128 filters: 1 instance
- Max Pooling Layers:
    - MaxPooling2D layer: 3 instances
- Flatten Layer:
    - Flatten layer: 1 instance.
- Dense Layers:
    - Dense layer with 128 neurons: 1 instance
    - Dense layer with 24 neurons: 1 instance



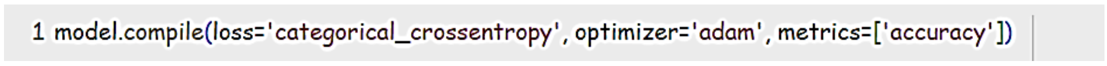
```python
model = keras.models.Sequential()
model.add(keras.layers.Conv2D(32, (5, 5), padding='same', activation='relu', input_shape=(28, 28, 1)))
model.add(keras.layers.MaxPooling2D(pool_size=(2, 2)))
model.add(keras.layers.Conv2D(64, (5, 5), padding='same', activation='relu'))
model.add(keras.layers.MaxPooling2D(pool_size=(2, 2)))
model.add(keras.layers.Conv2D(128, (5, 5), padding='same', activation='relu'))
model.add(keras.layers.MaxPooling2D(pool_size=(2, 2)))
model.add(keras.layers.Flatten())
model.add(keras.layers.Dense(128, activation='relu'))
model.add(keras.layers.Dense(24, activation='softmax'))
```

```python
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 28, 28, 32)        832

 max_pooling2d (MaxPooling2D  (None, 14, 14, 32)       0
 )

 conv2d_1 (Conv2D)           (None, 14, 14, 64)        51264

 max_pooling2d_1 (MaxPooling  (None, 7, 7, 64)         0
 2D)

 conv2d_2 (Conv2D)           (None, 7, 7, 128)         204928

 max_pooling2d_2 (MaxPooling  (None, 3, 3, 128)        0
 2D)

 flatten (Flatten)           (None, 1152)              0

 dense (Dense)               (None, 128)               147584

 dense_1 (Dense)             (None, 24)                3096

=================================================================
Total params: 407,704
Trainable params: 407,704
Non-trainable params: 0
_________________________________________________________________
```

Figure 11: Code Snippet 5

6. Compile the model using loss, optimizer, and metrics functions.



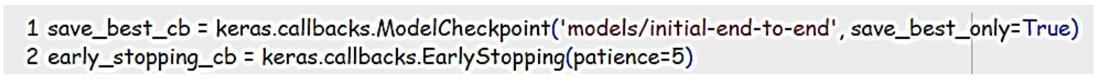
```
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
```

Figure 12:Code Snippet 6

7. Next, checkpoints are created:

   ModelCheckpoint: Saves best model during training at each epoch.

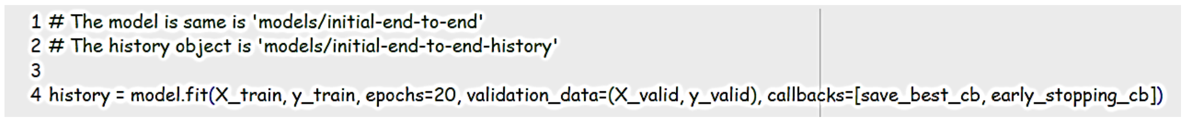
   EarlyStopping:.Interrupts training when there is no progress after a few epochs.



```
save_best_cb = keras.callbacks.ModelCheckpoint('models/initial-end-to-end', save_best_only=True)
early_stopping_cb = keras.callbacks.EarlyStopping(patience=5)
```

Figure 13: Code Snippet 7

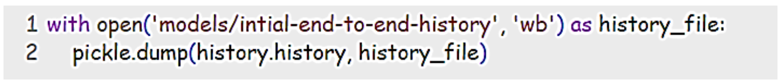
8. Finding patterns



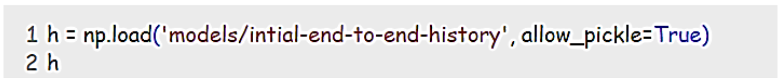
```
# The model is same is 'models/initial-end-to-end'
# The history object is 'models/initial-end-to-end-history'

history = model.fit(X_train, y_train, epochs=20, validation_data=(X_valid, y_valid), callbacks=[save_best_cb, early_stopping_cb])
```

Figure 14: Code Snippet 8

9. Reviewing the model training using the history object as it contains the loss and specified metrics obtained during training. This information is used to obtain the learning curves and access the training process and the model's performance at each epoch.



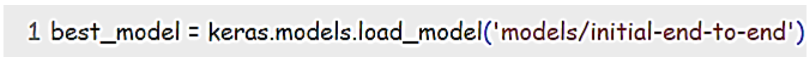
```
with open('models/intial-end-to-end-history', 'wb') as history_file:
    pickle.dump(history.history, history_file)
```



```
h = np.load('models/intial-end-to-end-history', allow_pickle=True)
h
```

Figure 15: Code Snippet 9

10. Retrieve the best model obtained during training.



```
best_model = keras.models.load_model('models/initial-end-to-end')
```

Figure 16: Code Snippet 10

11. Plotting training loss and its corrections

```
fig, ax = plt.subplots(figsize=(10, 5))
n_epochs = len(h['loss'])
ax.plot(range(1, n_epochs+1), h['loss'], color='b', label='train_loss')
ax.plot(range(1, n_epochs+1), h['val_loss'], color='c', label='val_loss')
ax.plot(range(1, n_epochs+1), h['accuracy'], color='b', label='train_accuracy', linestyle='--')
ax.plot(range(1, n_epochs+1), h['val_accuracy'], color='c', label='val_accuracy', linestyle='--')
ax.set_xticks(range(1, n_epochs+1))
ax.legend()
```

```
<matplotlib.legend.Legend at 0x16c5dc26580>
```

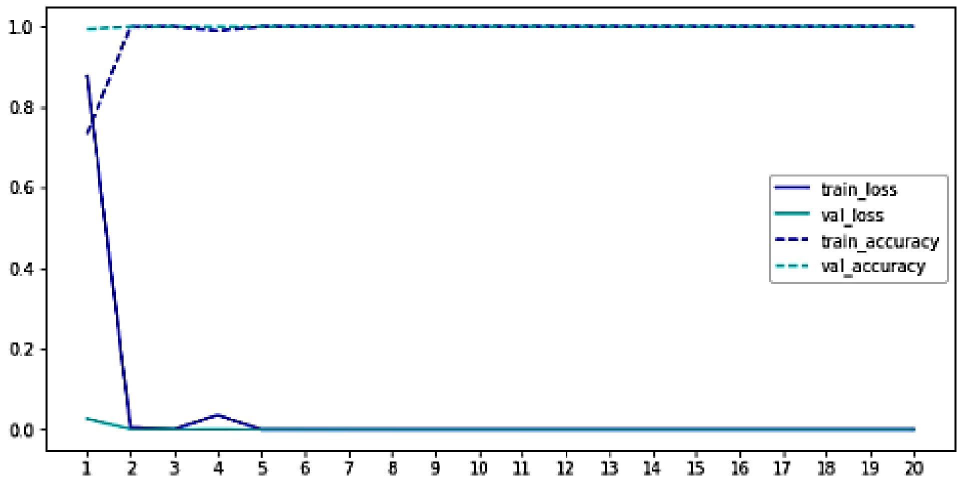


Figure 17: Code Snippet 11

```
]
# Training Loss Correction

fig, ax = plt.subplots(figsize=(10, 5))
n_epochs = len(h['loss'])

# Shift training loss by 0.5 as training loss is measured during the epoch and validation loss is measured after the epoch

x_loss = np.arange(n_epochs+1)-0.5
ax.plot(x_loss[x_loss >= 0], h['loss'], color='b', label='train_loss')
ax.plot(range(1, n_epochs+1), h['val_loss'], color='r', label='val_loss')
ax.plot(range(1, n_epochs+1), h['accuracy'], color='b', label='train_accuracy', linestyle='--')
ax.plot(range(1, n_epochs+1), h['val_accuracy'], color='r', label='val_accuracy', linestyle='--')
ax.set_xlim(0, n_epochs)
ax.set_xticks(range(1, n_epochs+1))
ax.legend()
```

```
<matplotlib.legend.Legend at 0x16c5db98fa0>
```

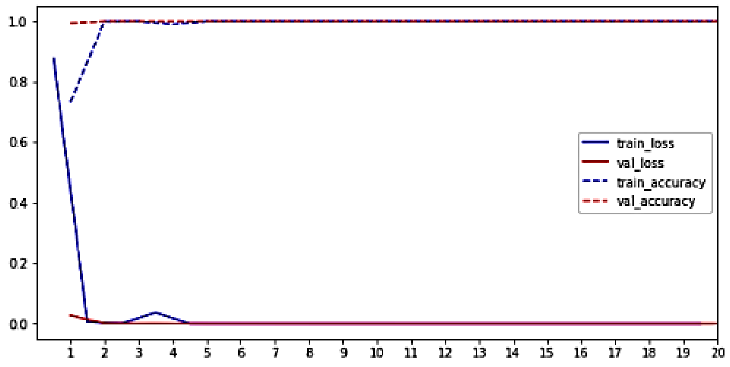
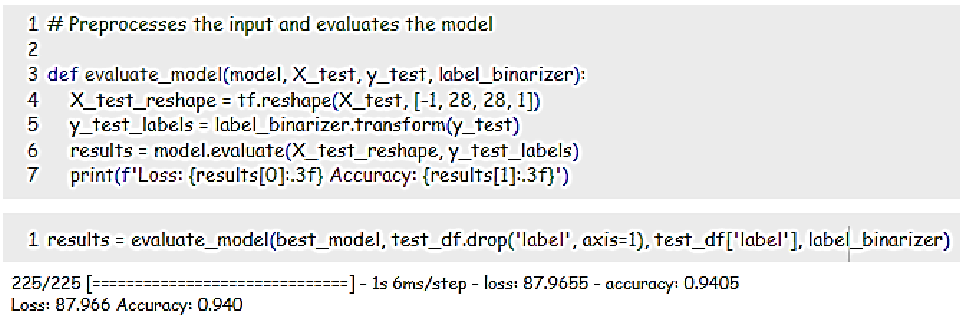


Figure 18: Code Snippet 12

12. Evaluating the model



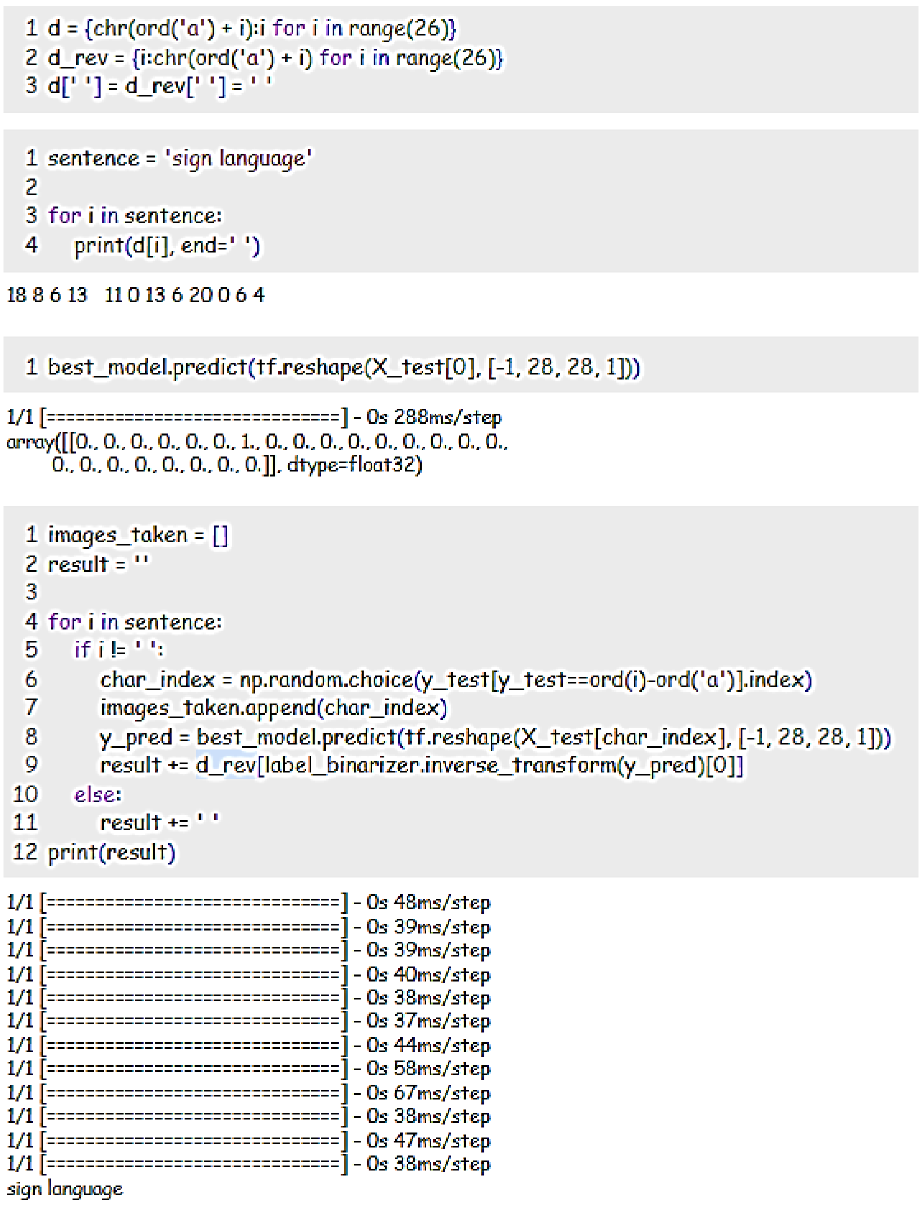
```
# Preprocesses the input and evaluates the model

def evaluate_model(model, X_test, y_test, label_binarizer):
    X_test_reshape = tf.reshape(X_test, [-1, 28, 28, 1])
    y_test_labels = label_binarizer.transform(y_test)
    results = model.evaluate(X_test_reshape, y_test_labels)
    print(f'Loss: {results[0]:.3f} Accuracy: {results[1]:.3f}')
```

```
results = evaluate_model(best_model, test_df.drop('label', axis=1), test_df['label'], label_binarizer)
```

```
225/225 [==============================] - 1s 6ms/step - loss: 87.9655 - accuracy: 0.9405
Loss: 87.966 Accuracy: 0.940
```

Figure 19: Code Snippet 13

13. Converting Sentences to Images



```
d = {chr(ord('a') + i):i for i in range(26)}
d_rev = {i:chr(ord('a') + i) for i in range(26)}
d[' '] = d_rev[' '] = ' '
```

```
sentence = 'sign language'

for i in sentence:
    print(d[i], end=' ')
```

```
18 8 6 13   11 0 13 6 20 0 6 4
```

```
best_model.predict(tf.reshape(X_test[0], [-1, 28, 28, 1]))
```

```
1/1 [==============================] - 0s 288ms/step
array([[0., 0., 0., 0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
        0., 0., 0., 0., 0., 0., 0., 0.]], dtype=float32)
```

```
images_taken = []
result = ''

for i in sentence:
    if i != ' ':
        char_index = np.random.choice(y_test[y_test==ord(i)-ord('a')].index)
        images_taken.append(char_index)
        y_pred = best_model.predict(tf.reshape(X_test[char_index], [-1, 28, 28, 1]))
        result += d_rev[label_binarizer.inverse_transform(y_pred)[0]]
    else:
        result += ' '
print(result)
```

```
1/1 [==============================] - 0s 48ms/step
1/1 [==============================] - 0s 39ms/step
1/1 [==============================] - 0s 39ms/step
1/1 [==============================] - 0s 40ms/step
1/1 [==============================] - 0s 38ms/step
1/1 [==============================] - 0s 37ms/step
1/1 [==============================] - 0s 44ms/step
1/1 [==============================] - 0s 58ms/step
1/1 [==============================] - 0s 67ms/step
1/1 [==============================] - 0s 38ms/step
1/1 [==============================] - 0s 47ms/step
1/1 [==============================] - 0s 38ms/step
sign language
```

```python
# Visualizing the test images
images_taken_dup = list(reversed(images_taken))
for word in sentence.split():
    fig, ax = plt.subplots(1, len(word), figsize=(20, 20))
    for i in range(len(word)):
        ax[i].imshow(X_test[images_taken_dup.pop()], cmap='gray')
        ax[i].set_title(word[i])
```

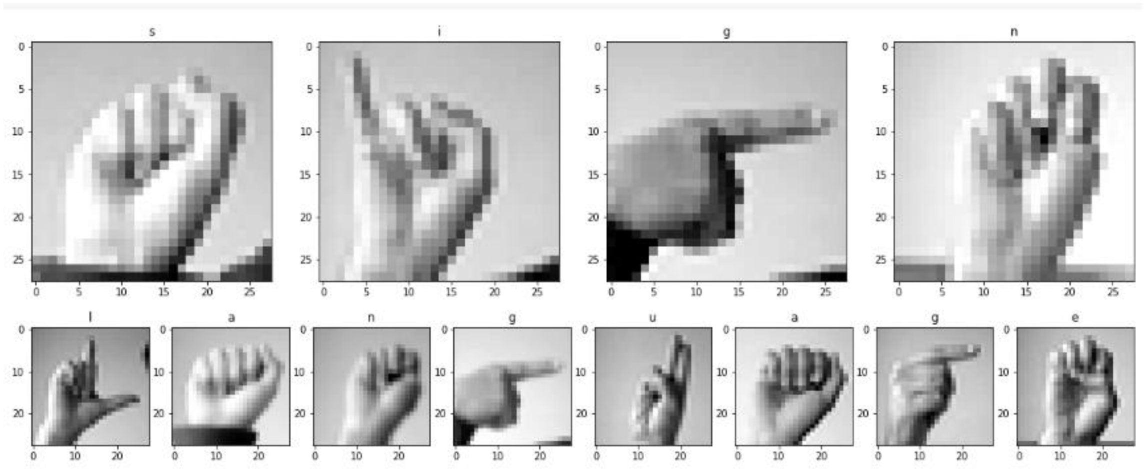
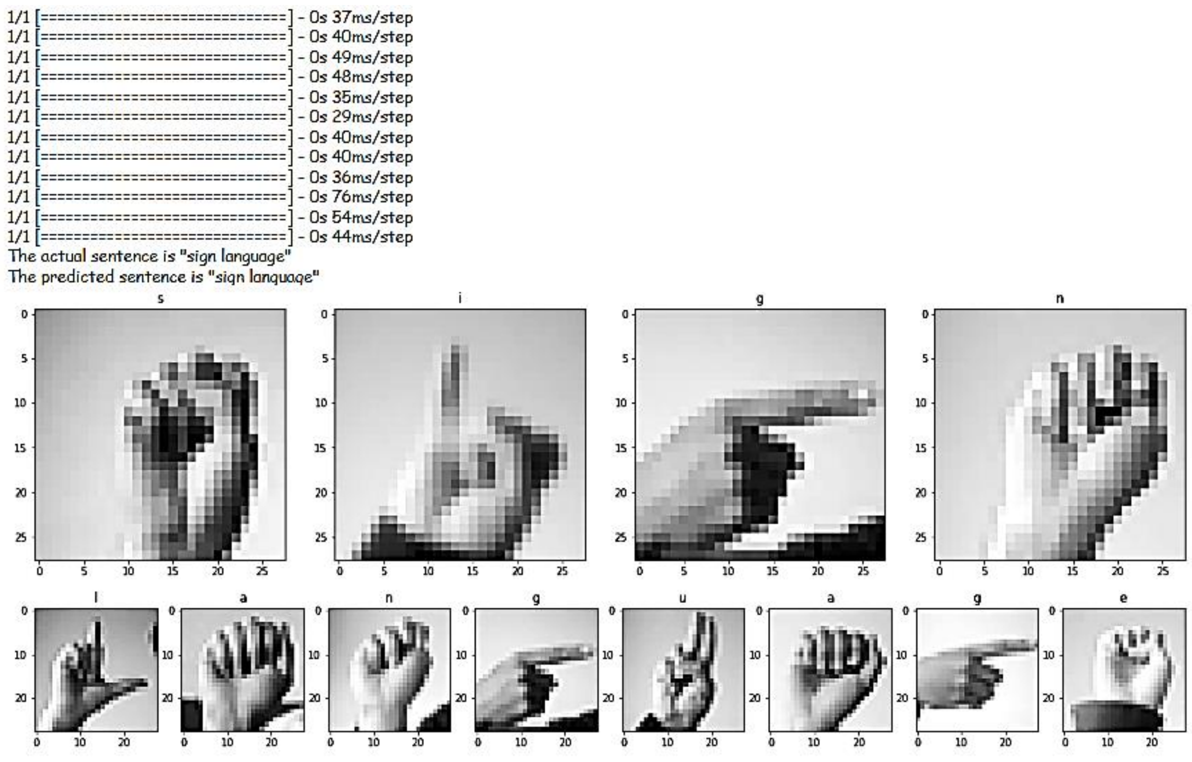


Figure 20: Code Snippet 14

14. Checking the model with respect to Test Data

```python
def test_on_sentence(model, sentence, X_test, y_test, label_binarizer, figsize=(20, 20)):
    # Random images are taken from X_test along with the corresponding labels in y_test
    # based on the letters in the sentence.
    # These images are fed to the model and its output is printed

    sentence = sentence.lower()

    d = {chr(ord('a') + i):i for i in range(26)}
    d_rev = {i:chr(ord('a') + i) for i in range(26)}
    d[' '] = d_rev[' '] = ' '


    images_taken = []
    result = ''

    X_test_reshape = tf.reshape(X_test, [-1, 28, 28, 1])


    for i in sentence:
        if i != ' ':
            char_index = np.random.choice(y_test[y_test==ord(i)-ord('a')].index)
            images_taken.append(char_index)
            y_pred = model.predict(tf.reshape(X_test_reshape[char_index], [1, 28, 28, 1]))
            result += d_rev[label_binarizer.inverse_transform(y_pred)[0]]
        else:
            result += ' '

    print(f'The actual sentence is "{sentence}"')
    print(f'The predicted sentence is "{result}"')

    images_taken.reverse()
    for word in sentence.split():
        fig, ax = plt.subplots(1, len(word), figsize=figsize)
        for i in range(len(word)):
            ax[i].imshow(X_test_reshape[images_taken.pop()], cmap='gray')
            ax[i].set_title(word[i])
```

```python
test_on_sentence(best_model, 'sign language', test_df.drop('label', axis=1), test_df['label'], label_binarizer)
```

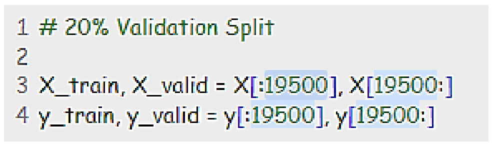


```
1/1 [==============================] - 0s 37ms/step
1/1 [==============================] - 0s 40ms/step
1/1 [==============================] - 0s 49ms/step
1/1 [==============================] - 0s 48ms/step
1/1 [==============================] - 0s 35ms/step
1/1 [==============================] - 0s 29ms/step
1/1 [==============================] - 0s 40ms/step
1/1 [==============================] - 0s 40ms/step
1/1 [==============================] - 0s 36ms/step
1/1 [==============================] - 0s 76ms/step
1/1 [==============================] - 0s 54ms/step
1/1 [==============================] - 0s 44ms/step
The actual sentence is "sign language"
The predicted sentence is "sign language"
```

Figure 21: Code Snippet 15

15. Hyperparameter Tuning

For this there is a 20% validation split



```
# 20% Validation Split

X_train, X_valid = X[:19500], X[19500:]
y_train, y_valid = y[:19500], y[19500:]
```

Figure 22: Code Snippet 16

a. Convolutional and Max-Pooling Pairs:

The depth of the networks increases as pairs are stacked, making it easier for the model to recognize intricate image patterns. Yet, when an excessive number of layers are stacked, there is an adverse consequence on the exhibition by the model, and the quantity of teachable boundaries of the model likewise increment definitely, expanding the preparation time.

Convolution and Max Pooling Pairs

Before flattening

1. For pair = 1 -> Output to the dense layer will be of the shape `(None, 14, 14, 32)`
2. For pair = 2 -> Output to the dense layer will be of the shape `(None, 7, 7, 64)`
3. For pair = 3 -> Output to the dense layer will be of the shape `(None, 3, 3, 96)`
4. For pair = 4 -> Output to the dense layer will be of the shape `(None, 1, 1, 128)`

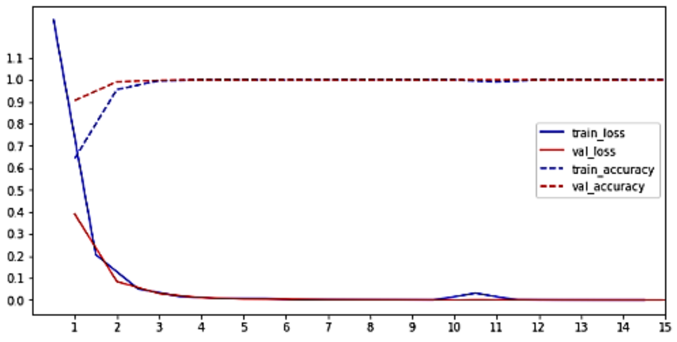
As the output shape rapidly decreases for the pair = 4 it is better to choose among the pair = 1, 2 or 3

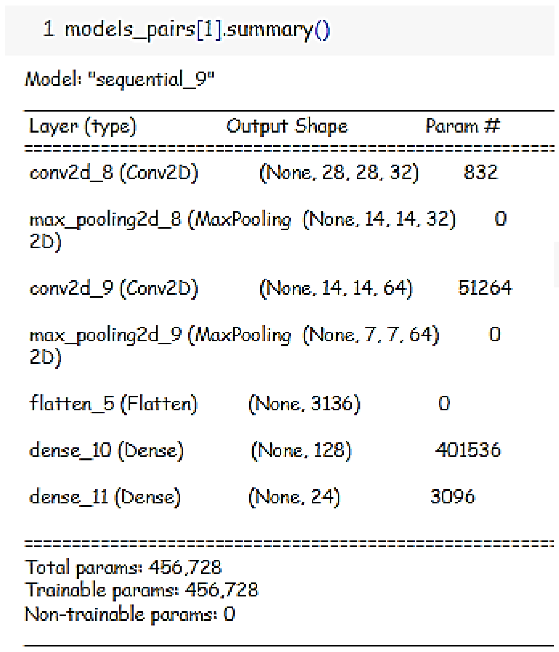
```python
# Models
# 'models/experiment-1-1'
# 'models/experiment-1-2'
# 'models/experiment-1-3'

# History objects
# 'models/experiment-1-1-history'
# 'models/experiment-1-2-history'
# 'models/experiment-1-3-history'

n_pairs = 3
models_pairs = [keras.models.Sequential() for i in range(n_pairs)]
early_stopping_cb = keras.callbacks.EarlyStopping(patience=5)

for n in range(1, n_pairs+1):
    models_pairs[n-1].add(keras.layers.Conv2D(32, (5, 5), padding='same', activation='relu', input_shape=(28, 28, 1)))
    models_pairs[n-1].add(keras.layers.MaxPooling2D(pool_size=(2, 2)))
    for i in range(1, n):
        models_pairs[n-1].add(keras.layers.Conv2D(32*(i+1), (5, 5), padding='same', activation='relu'))
        models_pairs[n-1].add(keras.layers.MaxPooling2D(pool_size=(2, 2)))
    models_pairs[n-1].add(keras.layers.Flatten())
    models_pairs[n-1].add(keras.layers.Dense(128, activation='relu'))
    models_pairs[n-1].add(keras.layers.Dense(24, activation='softmax'))
    models_pairs[n-1].compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
    save_best_cb = keras.callbacks.ModelCheckpoint(f'models/experiment-1-{n}', save_best_only=True)
    history = models_pairs[n-1].fit(X_train, y_train, epochs=15, validation_data=(X_valid, y_valid), callbacks=[save_best_cb, early_stopping_cb])
    with open(f'models/experiment-1-{n}-history', 'wb') as history_file:
        pickle.dump(history.history, history_file)
```

```python
models_pairs[0].summary()
```

```
Model: "sequential_8"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_7 (Conv2D)           (None, 28, 28, 32)        832

 max_pooling2d_7 (MaxPooling  (None, 14, 14, 32)       0
 2D)

 flatten_4 (Flatten)         (None, 6272)              0

 dense_8 (Dense)             (None, 128)               802944

 dense_9 (Dense)             (None, 24)                3096

=================================================================
Total params: 806,872
Trainable params: 806,872
Non-trainable params: 0
_________________________________________________________________
```

```python
get_train_val_plots(h_1_1, yticks=np.arange(0, 1.2, 0.1))
```

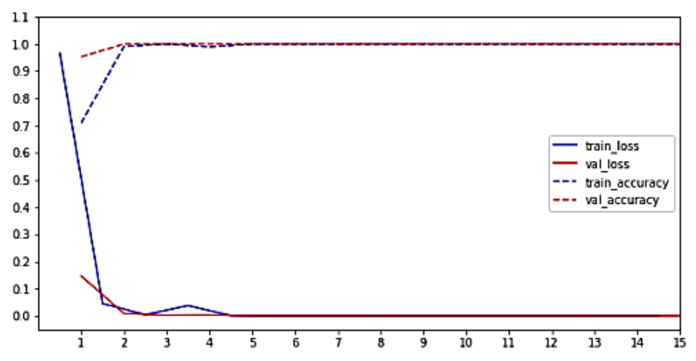


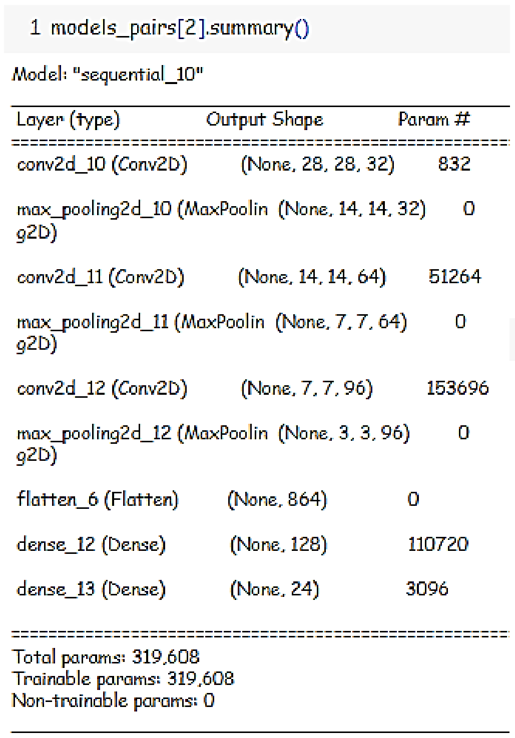


```
1 models_pairs[1].summary()
```

```
Model: "sequential_9"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_8 (Conv2D)            (None, 28, 28, 32)        832

max_pooling2d_8 (MaxPooling  (None, 14, 14, 32)        0
2D)

conv2d_9 (Conv2D)            (None, 14, 14, 64)        51264

max_pooling2d_9 (MaxPooling  (None, 7, 7, 64)          0
2D)

flatten_5 (Flatten)          (None, 3136)              0

dense_10 (Dense)             (None, 128)               401536

dense_11 (Dense)             (None, 24)                3096

=================================================================
Total params: 456,728
Trainable params: 456,728
Non-trainable params: 0
_________________________________________________________________
```

```
1 get_train_val_plots(h_1_2, yticks=np.arange(0, 1.2, 0.1))
```





```
1 models_pairs[2].summary()
```

```
Model: "sequential_10"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_10 (Conv2D)           (None, 28, 28, 32)        832

max_pooling2d_10 (MaxPoolin  (None, 14, 14, 32)        0
g2D)

conv2d_11 (Conv2D)           (None, 14, 14, 64)        51264

max_pooling2d_11 (MaxPoolin  (None, 7, 7, 64)          0
g2D)

conv2d_12 (Conv2D)           (None, 7, 7, 96)          153696

max_pooling2d_12 (MaxPoolin  (None, 3, 3, 96)          0
g2D)

flatten_6 (Flatten)          (None, 864)               0

dense_12 (Dense)             (None, 128)               110720

dense_13 (Dense)             (None, 24)                3096

=================================================================
Total params: 319,608
Trainable params: 319,608
Non-trainable params: 0
_________________________________________________________________
```

```
1 get_train_val_plots(h_1_3, yticks=np.arange(0, 1.2, 0.1))
```

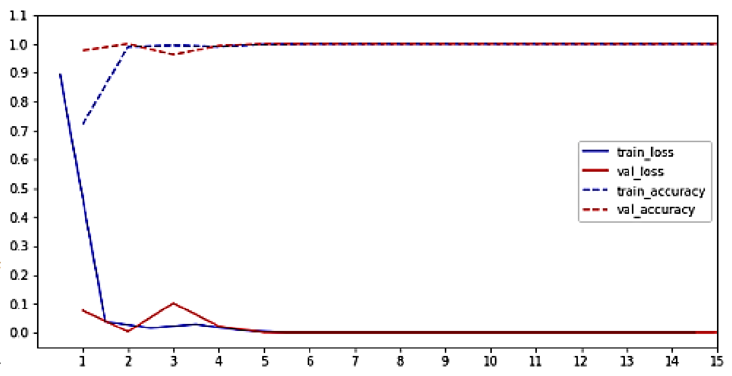
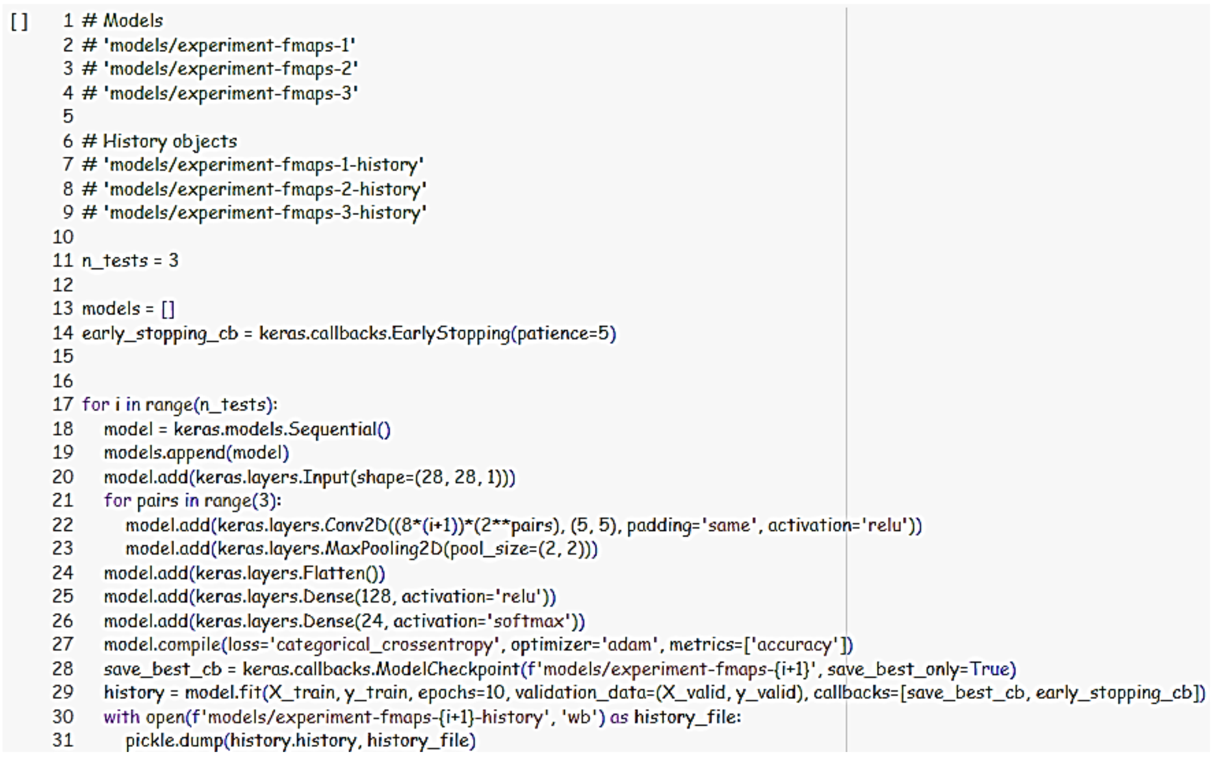


Figure 23: Code Snippet 17

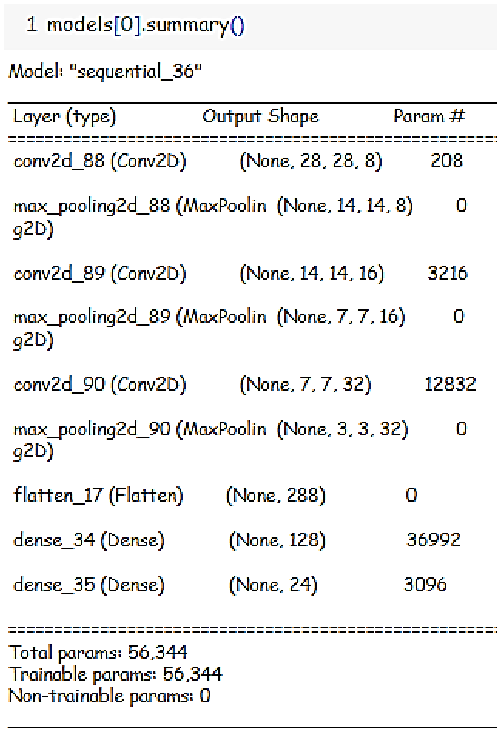
Model 3 has the least loss on validation data.

b. Filters

Filters determine the number of output feature maps because they serve as a pattern and can identify patterns in multiple images. Expanding the channels

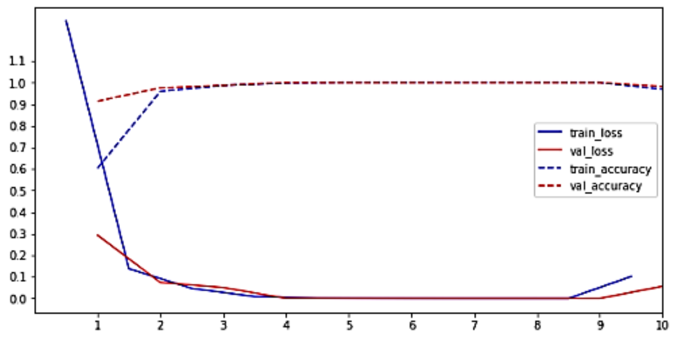


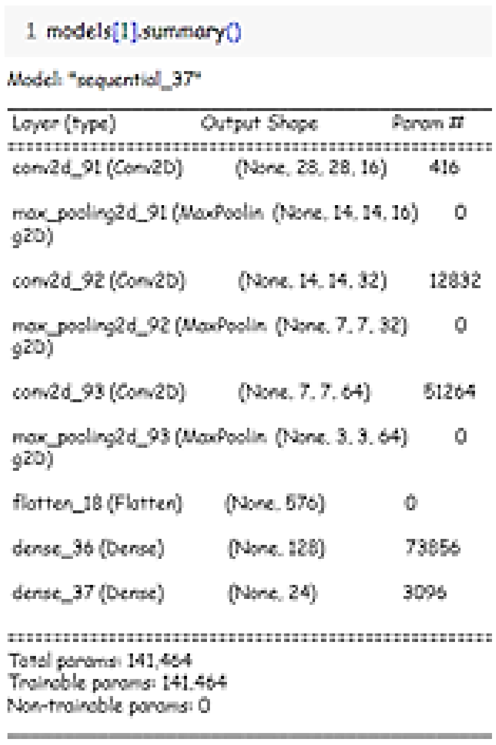
```
[ ]
# Models
# 'models/experiment-fmaps-1'
# 'models/experiment-fmaps-2'
# 'models/experiment-fmaps-3'

# History objects
# 'models/experiment-fmaps-1-history'
# 'models/experiment-fmaps-2-history'
# 'models/experiment-fmaps-3-history'

n_tests = 3

models = []
early_stopping_cb = keras.callbacks.EarlyStopping(patience=5)


for i in range(n_tests):
    model = keras.models.Sequential()
    models.append(model)
    model.add(keras.layers.Input(shape=(28, 28, 1)))
    for pairs in range(3):
        model.add(keras.layers.Conv2D((8*(i+1))*(2**pairs), (5, 5), padding='same', activation='relu'))
        model.add(keras.layers.MaxPooling2D(pool_size=(2, 2)))
    model.add(keras.layers.Flatten())
    model.add(keras.layers.Dense(128, activation='relu'))
    model.add(keras.layers.Dense(24, activation='softmax'))
    model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
    save_best_cb = keras.callbacks.ModelCheckpoint(f'models/experiment-fmaps-{i+1}', save_best_only=True)
    history = model.fit(X_train, y_train, epochs=10, validation_data=(X_valid, y_valid), callbacks=[save_best_cb, early_stopping_cb])
    with open(f'models/experiment-fmaps-{i+1}-history', 'wb') as history_file:
        pickle.dump(history.history, history_file)
```



```
models[0].summary()
```

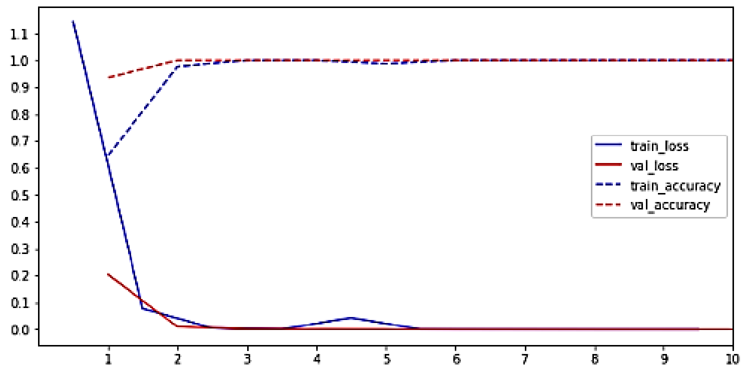
```
Model: "sequential_36"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_88 (Conv2D)          (None, 28, 28, 8)         208

 max_pooling2d_88 (MaxPoolin  (None, 14, 14, 8)        0
 g2D)

 conv2d_89 (Conv2D)          (None, 14, 14, 16)        3216

 max_pooling2d_89 (MaxPoolin  (None, 7, 7, 16)         0
 g2D)

 conv2d_90 (Conv2D)          (None, 7, 7, 32)          12832

 max_pooling2d_90 (MaxPoolin  (None, 3, 3, 32)         0
 g2D)

 flatten_17 (Flatten)        (None, 288)               0

 dense_34 (Dense)            (None, 128)               36992

 dense_35 (Dense)            (None, 24)                3096

=================================================================
Total params: 56,344
Trainable params: 56,344
Non-trainable params: 0
_________________________________________________________________
```

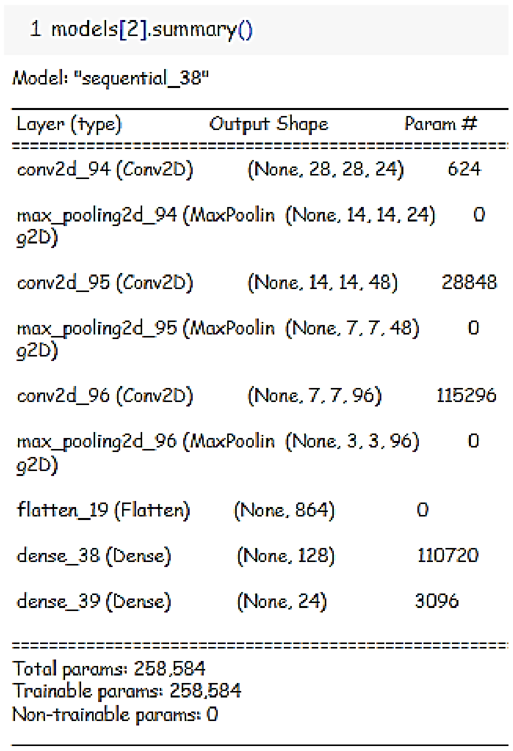




```
1 models[1].summary()
```

```
Model: "sequential_37"
_________________________________________________________________
Layer (type)                Output Shape              Param #
=================================================================
conv2d_91 (Conv2D)          (None, 28, 28, 16)        416

max_pooling2d_91 (MaxPoolin (None, 14, 14, 16)        0
g2D)

conv2d_92 (Conv2D)          (None, 14, 14, 32)        12832

max_pooling2d_92 (MaxPoolin (None, 7, 7, 32)          0
g2D)

conv2d_93 (Conv2D)          (None, 7, 7, 64)          51264

max_pooling2d_93 (MaxPoolin (None, 3, 3, 64)          0
g2D)

flatten_18 (Flatten)        (None, 576)               0

dense_36 (Dense)            (None, 128)               73856

dense_37 (Dense)            (None, 24)                3096

=================================================================
Total params: 141,464
Trainable params: 141,464
Non-trainable params: 0
_________________________________________________________________
```





```
1 models[2].summary()
```

```
Model: "sequential_38"
_________________________________________________________________
Layer (type)                Output Shape              Param #
=================================================================
conv2d_94 (Conv2D)          (None, 28, 28, 24)        624

max_pooling2d_94 (MaxPoolin (None, 14, 14, 24)        0
g2D)

conv2d_95 (Conv2D)          (None, 14, 14, 48)        28848

max_pooling2d_95 (MaxPoolin (None, 7, 7, 48)          0
g2D)

conv2d_96 (Conv2D)          (None, 7, 7, 96)          115296

max_pooling2d_96 (MaxPoolin (None, 3, 3, 96)          0
g2D)

flatten_19 (Flatten)        (None, 864)               0

dense_38 (Dense)            (None, 128)               110720

dense_39 (Dense)            (None, 24)                3096

=================================================================
Total params: 258,584
Trainable params: 258,584
Non-trainable params: 0
_________________________________________________________________
```

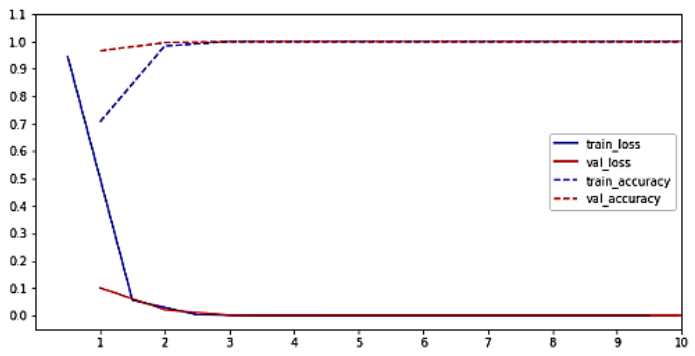
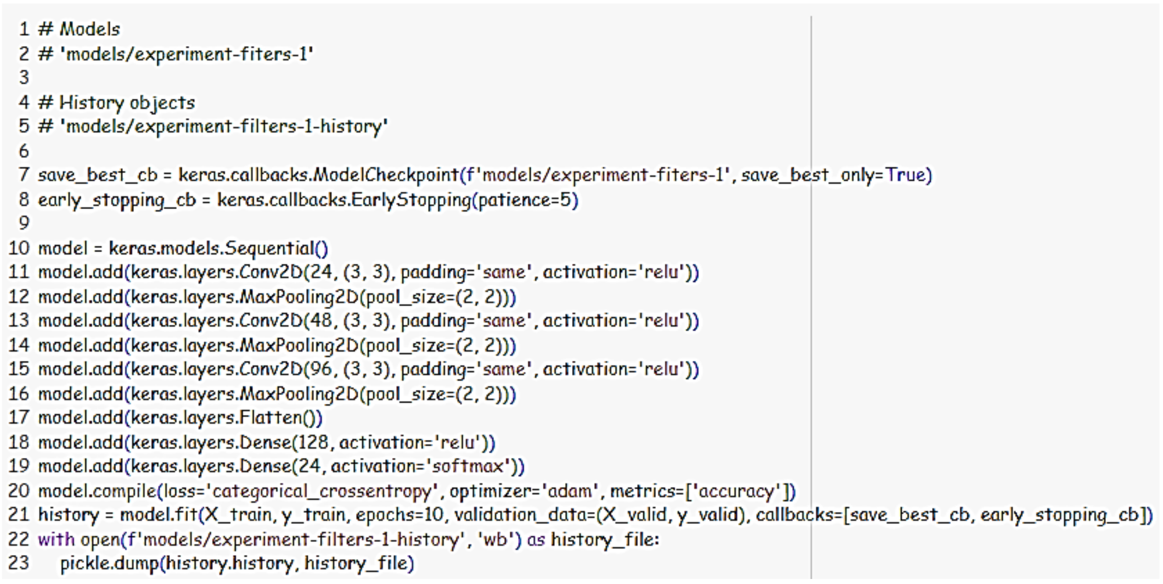


Figure 24: Code Snippet 18

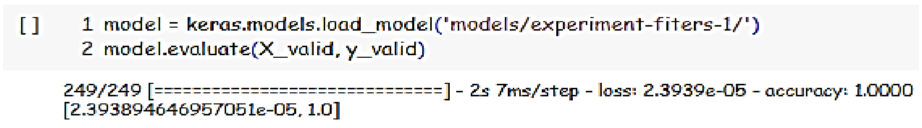
Model 3 has the least loss on validation data.

c. Filter Size

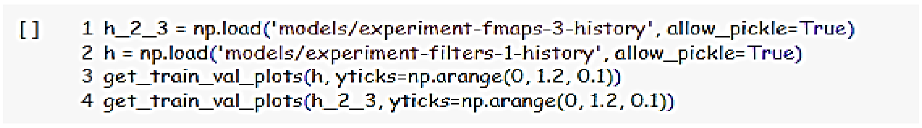
Numerous convolutional layers can be used with lower channel sizes rather than a solitary convolution layer comprised of channels with greater sizes, for example, (7x7, 9x9). This will without a doubt build the model's exhibition in light of the fact that more profound organizations are better ready to identify muddled designs.



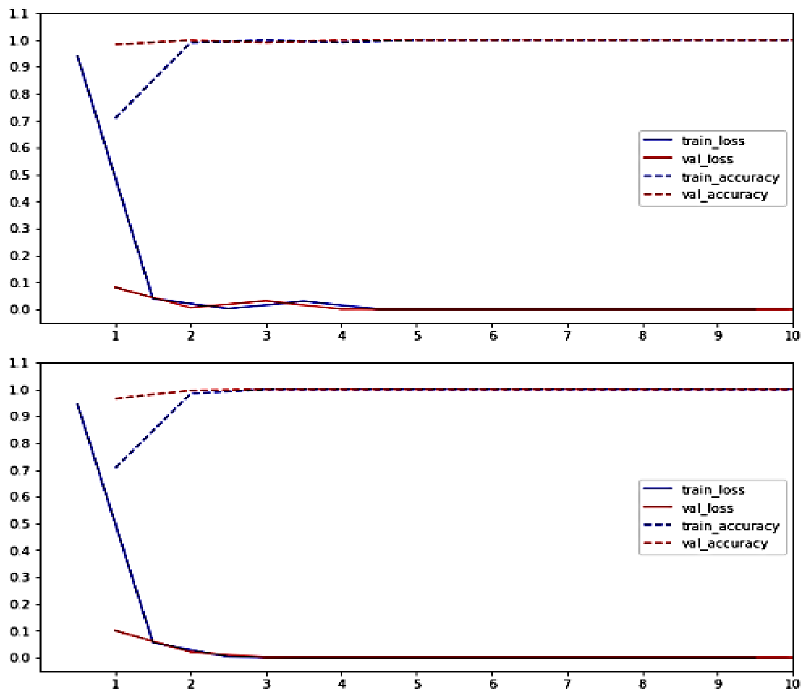
```
# Models
# 'models/experiment-fiters-1'

# History objects
# 'models/experiment-filters-1-history'

save_best_cb = keras.callbacks.ModelCheckpoint(f'models/experiment-fiters-1', save_best_only=True)
early_stopping_cb = keras.callbacks.EarlyStopping(patience=5)

model = keras.models.Sequential()
model.add(keras.layers.Conv2D(24, (3, 3), padding='same', activation='relu'))
model.add(keras.layers.MaxPooling2D(pool_size=(2, 2)))
model.add(keras.layers.Conv2D(48, (3, 3), padding='same', activation='relu'))
model.add(keras.layers.MaxPooling2D(pool_size=(2, 2)))
model.add(keras.layers.Conv2D(96, (3, 3), padding='same', activation='relu'))
model.add(keras.layers.MaxPooling2D(pool_size=(2, 2)))
model.add(keras.layers.Flatten())
model.add(keras.layers.Dense(128, activation='relu'))
model.add(keras.layers.Dense(24, activation='softmax'))
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
history = model.fit(X_train, y_train, epochs=10, validation_data=(X_valid, y_valid), callbacks=[save_best_cb, early_stopping_cb])
with open(f'models/experiment-filters-1-history', 'wb') as history_file:
    pickle.dump(history.history, history_file)
```



```
[ ]  model = keras.models.load_model('models/experiment-fiters-1/')
     model.evaluate(X_valid, y_valid)

249/249 [==============================] - 2s 7ms/step - loss: 2.3939e-05 - accuracy: 1.0000
[2.393894646957051e-05, 1.0]
```



```
[ ]  h_2_3 = np.load('models/experiment-fmaps-3-history', allow_pickle=True)
     h = np.load('models/experiment-filters-1-history', allow_pickle=True)
     get_train_val_plots(h, yticks=np.arange(0, 1.2, 0.1))
     get_train_val_plots(h_2_3, yticks=np.arange(0, 1.2, 0.1))
```



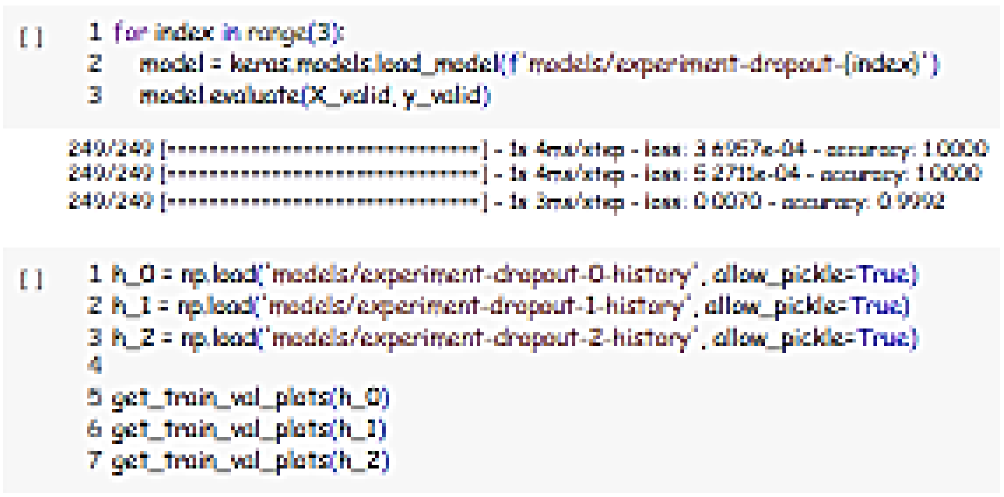
We choose to use filter sizes of (5x5)

Figure 25: Code Snippet 19

d. Dropout

Dropout fills in as a regularizer and forestalls overfitting in the model. The dropout layer eliminates some neurons' contributions to the subsequent layer, while others remain unchanged. The dropout rate determines how likely it is that a given neuron's contribution will be lost.

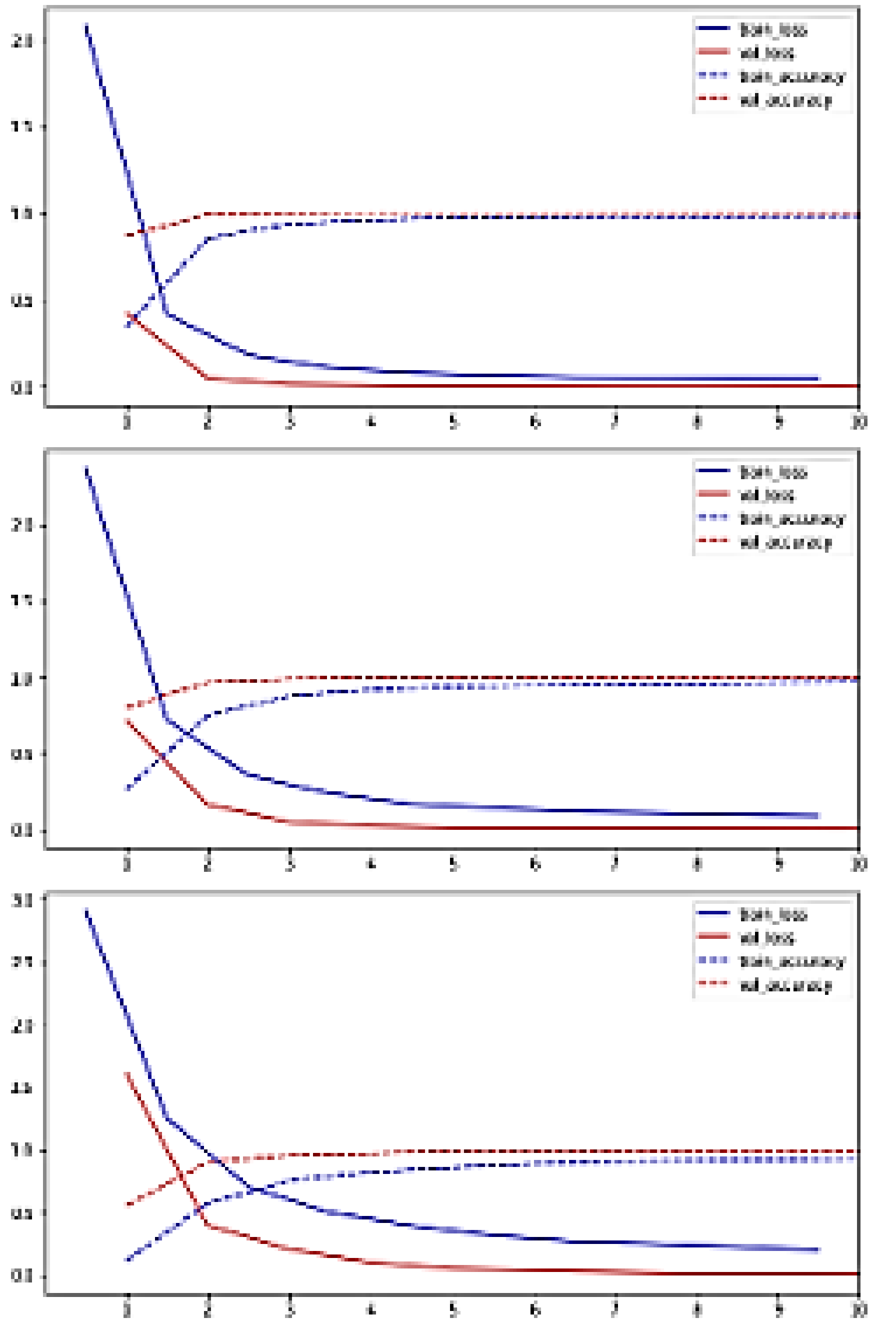
```
# Models
# 'models/experiment-dropout-0'
# 'models/experiment-dropout-1'
# 'models/experiment-dropout-2'

# History objects
# 'models/experiment-dropout-0-history'
# 'models/experiment-dropout-1-history'
# 'models/experiment-dropout-2-history'

early_stopping_cb = keras.callbacks.EarlyStopping(patience=5)

dropout_rates = [0.3, 0.4, 0.5]

for index, i in enumerate(dropout_rates):
  model = keras.models.Sequential()
  model.add(keras.layers.Conv2D(24, (5, 5), padding='same', activation='relu'))
  model.add(keras.layers.MaxPooling2D(pool_size=(2, 2)))
  model.add(keras.layers.Dropout(i))
  model.add(keras.layers.Conv2D(48, (5, 5), padding='same', activation='relu'))
  model.add(keras.layers.MaxPooling2D(pool_size=(2, 2)))
  model.add(keras.layers.Dropout(i))
  model.add(keras.layers.Conv2D(96, (5, 5), padding='same', activation='relu'))
  model.add(keras.layers.MaxPooling2D(pool_size=(2, 2)))
  model.add(keras.layers.Dropout(i))
  model.add(keras.layers.Flatten())
  model.add(keras.layers.Dense(128, activation='relu'))
  model.add(keras.layers.Dropout(i))
  model.add(keras.layers.Dense(24, activation='softmax'))
  model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
  save_best_cb = keras.callbacks.ModelCheckpoint(f'models/experiment-dropout-{index}', save_best_only=True)
  history = model.fit(X_train, y_train, epochs=10, validation_data=(X_valid, y_valid), callbacks=[save_best_cb, early_stopping_cb])
  with open(f'models/experiment-dropout-{index}-history', 'wb') as history_file:
    pickle.dump(history.history, history_file)
```



```
[ ]
for index in range(3):
    model = keras.models.load_model(f'models/experiment-dropout-{index}')
    model.evaluate(X_valid, y_valid)
```

```
249/249 [==============================] - 1s 4ms/step - loss: 3.6957e-04 - accuracy: 1.0000
249/249 [==============================] - 1s 4ms/step - loss: 5.2711e-04 - accuracy: 1.0000
249/249 [==============================] - 1s 3ms/step - loss: 0.0070 - accuracy: 0.9992
```

```
[ ]
h_0 = np.load('models/experiment-dropout-0-history', allow_pickle=True)
h_1 = np.load('models/experiment-dropout-1-history', allow_pickle=True)
h_2 = np.load('models/experiment-dropout-2-history', allow_pickle=True)

get_train_val_plots(h_0)
get_train_val_plots(h_1)
get_train_val_plots(h_2)
```

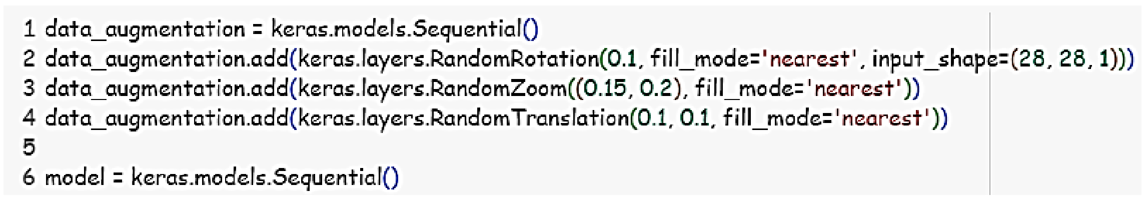


Select Model 1

Figure 26: Code Snippet 20

e. Data Augmentation

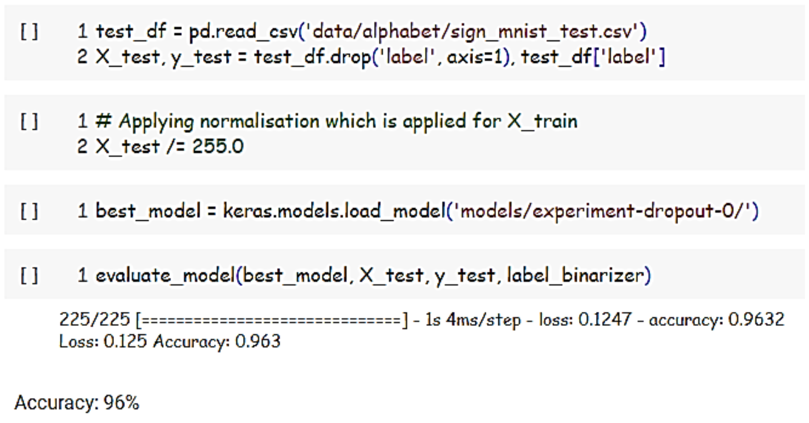
Duplicates can be made of the current photographs that are fundamentally adjusted utilizing information expansion, and afterward utilize those duplicates to prepare the model. Using these photos of items in various orientations, the model can identify items in various orientations.



```python
data_augmentation = keras.models.Sequential()
data_augmentation.add(keras.layers.RandomRotation(0.1, fill_mode='nearest', input_shape=(28, 28, 1)))
data_augmentation.add(keras.layers.RandomZoom((0.15, 0.2), fill_mode='nearest'))
data_augmentation.add(keras.layers.RandomTranslation(0.1, 0.1, fill_mode='nearest'))

model = keras.models.Sequential()
```

Figure 27: Code Snippet 21

16. Final Evaluation



```python
[ ]  test_df = pd.read_csv('data/alphabet/sign_mnist_test.csv')
     X_test, y_test = test_df.drop('label', axis=1), test_df['label']
```

```python
[ ]  # Applying normalisation which is applied for X_train
     X_test /= 255.0
```

```python
[ ]  best_model = keras.models.load_model('models/experiment-dropout-0/')
```

```python
[ ]  evaluate_model(best_model, X_test, y_test, label_binarizer)
```

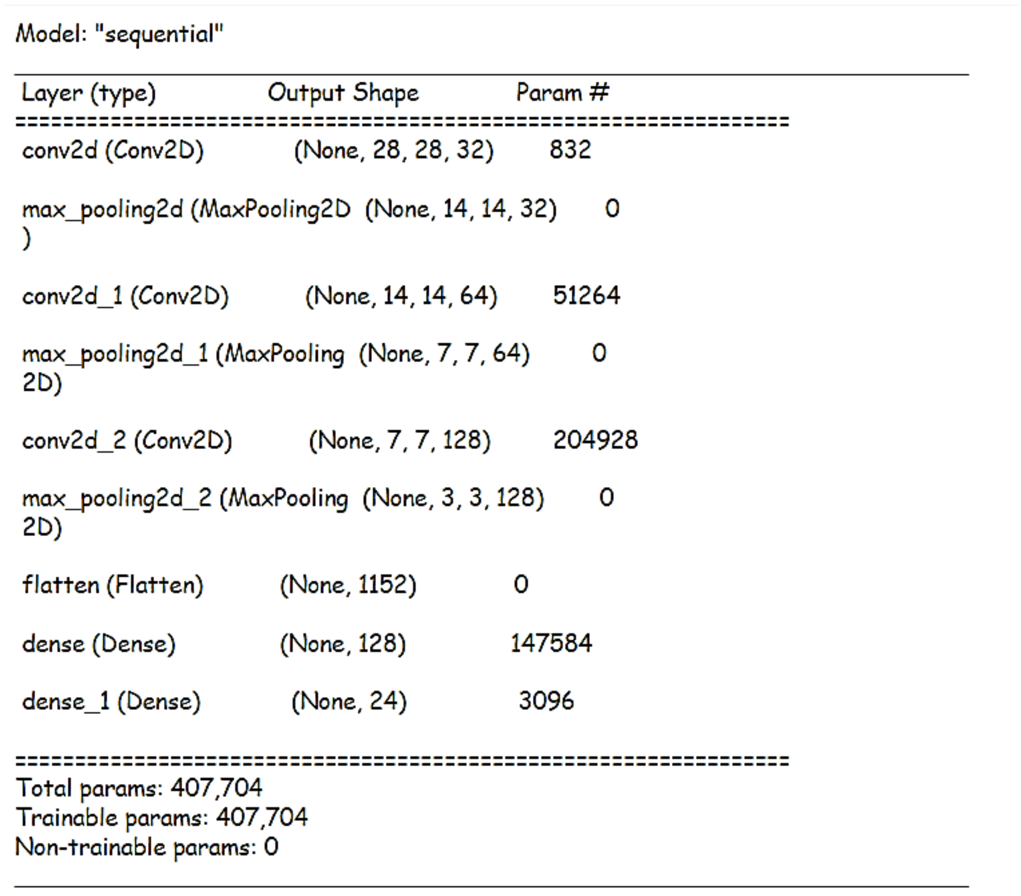
```
225/225 [==============================] - 1s 4ms/step - loss: 0.1247 - accuracy: 0.9632
Loss: 0.125 Accuracy: 0.963
```

Accuracy: 96%

Figure 28: Code Snippet 22

4. RESULTS AND DISCUSSIONS

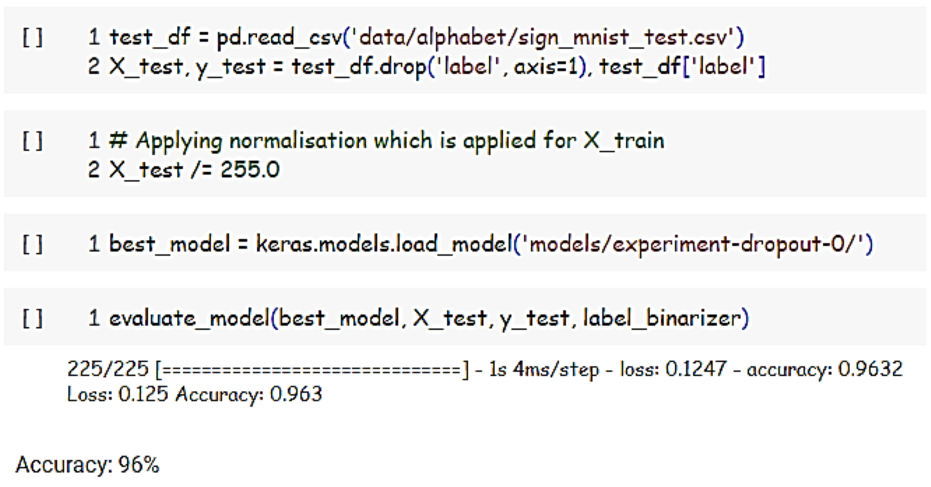
After a lot of testing the data and the CNN models with hyperparameter tuning, the best sequential model which can be built is:



```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 28, 28, 32)        832

 max_pooling2d (MaxPooling2D  (None, 14, 14, 32)       0
 )

 conv2d_1 (Conv2D)           (None, 14, 14, 64)        51264

 max_pooling2d_1 (MaxPooling  (None, 7, 7, 64)         0
 2D)

 conv2d_2 (Conv2D)           (None, 7, 7, 128)         204928

 max_pooling2d_2 (MaxPooling  (None, 3, 3, 128)        0
 2D)

 flatten (Flatten)           (None, 1152)              0

 dense (Dense)               (None, 128)               147584

 dense_1 (Dense)             (None, 24)                3096

=================================================================
Total params: 407,704
Trainable params: 407,704
Non-trainable params: 0
_________________________________________________________________
```

Figure 29: Final model

After training, the final model’s accuracy is **96%**.



```
[ ]  test_df = pd.read_csv('data/alphabet/sign_mnist_test.csv')
     X_test, y_test = test_df.drop('label', axis=1), test_df['label']
```

```
[ ]  # Applying normalisation which is applied for X_train
     X_test /= 255.0
```

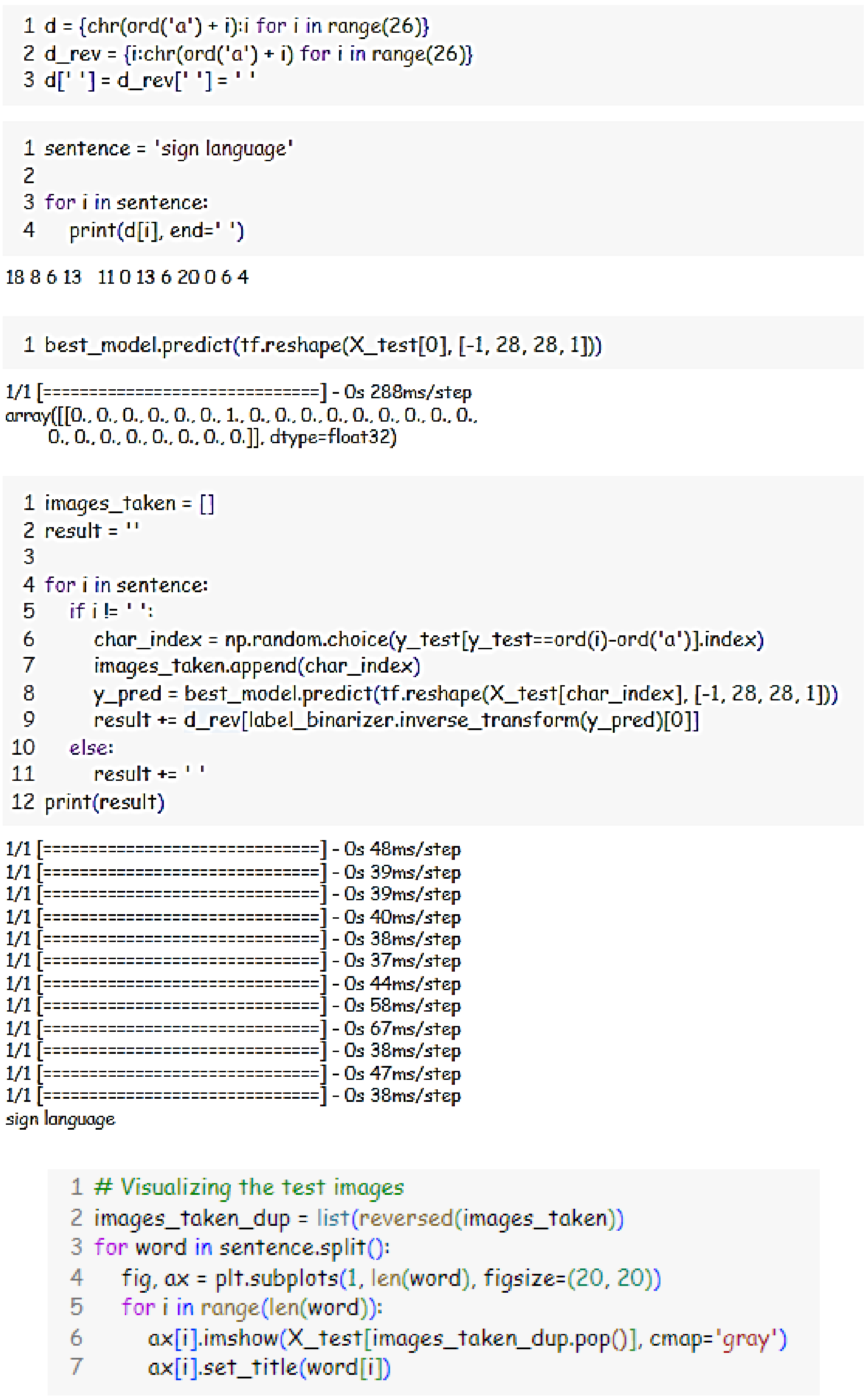
```
[ ]  best_model = keras.models.load_model('models/experiment-dropout-0/')
```

```
[ ]  evaluate_model(best_model, X_test, y_test, label_binarizer)

225/225 [==============================] - 1s 4ms/step - loss: 0.1247 - accuracy: 0.9632
Loss: 0.125 Accuracy: 0.963
```

Accuracy: 96%

Figure 30: Accuracy of the final model

This sign language recognition system, has been trained in such a way that an input sentence can be converted into a hand gesture sign language as shown below:



```python
d = {chr(ord('a') + i):i for i in range(26)}
d_rev = {i:chr(ord('a') + i) for i in range(26)}
d[' '] = d_rev[' '] = ' '
```

```python
sentence = 'sign language'

for i in sentence:
    print(d[i], end=' ')
```

```
18 8 6 13   11 0 13 6 20 0 6 4
```

```python
best_model.predict(tf.reshape(X_test[0], [-1, 28, 28, 1]))
```

```
1/1 [==============================] - 0s 288ms/step
array([[0., 0., 0., 0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
        0., 0., 0., 0., 0., 0., 0., 0.]], dtype=float32)
```

```python
images_taken = []
result = ''

for i in sentence:
    if i != ' ':
        char_index = np.random.choice(y_test[y_test==ord(i)-ord('a')].index)
        images_taken.append(char_index)
        y_pred = best_model.predict(tf.reshape(X_test[char_index], [-1, 28, 28, 1]))
        result += d_rev[label_binarizer.inverse_transform(y_pred)[0]]
    else:
        result += ' '
print(result)
```

```
1/1 [==============================] - 0s 48ms/step
1/1 [==============================] - 0s 39ms/step
1/1 [==============================] - 0s 39ms/step
1/1 [==============================] - 0s 40ms/step
1/1 [==============================] - 0s 38ms/step
1/1 [==============================] - 0s 37ms/step
1/1 [==============================] - 0s 44ms/step
1/1 [==============================] - 0s 58ms/step
1/1 [==============================] - 0s 67ms/step
1/1 [==============================] - 0s 38ms/step
1/1 [==============================] - 0s 47ms/step
1/1 [==============================] - 0s 38ms/step
sign language
```

```python
# Visualizing the test images
images_taken_dup = list(reversed(images_taken))
for word in sentence.split():
    fig, ax = plt.subplots(1, len(word), figsize=(20, 20))
    for i in range(len(word)):
        ax[i].imshow(X_test[images_taken_dup.pop()], cmap='gray')
        ax[i].set_title(word[i])
```

Figure 31: Converting Text to Image

5. SUMMARY AND CONCLUSION

5.1. SUMMARY OF ACHIEVEMENTS

The sign language recognition system developed using deep learning techniques for static image input format has achieved several remarkable milestones. Firstly, it successfully addresses the communication barriers encountered by individuals with hearing impairments by precisely recognizing and interpreting sign language gestures, with a specific emphasis on alphabet recognition. This breakthrough enables effective and seamless communication between individuals using sign language and those who may not possess proficiency in it.

Moreover, the system demonstrates the immense potential of deep learning algorithms in capturing intricate patterns and features within sign language gestures, resulting in exceptional accuracy and robustness in recognition.

The system's performance has been rigorously evaluated through extensive testing and assessment, utilizing the datasets. It has exhibited remarkable results, achieving high accuracy rates in accurately recognizing and classifying sign language alphabets from static images. This achievement serves as a testament to the system's efficacy in real-world scenarios, offering improved communication accessibility for individuals with hearing impairments.

Furthermore, the research has identified and successfully addressed various challenges associated with sign language recognition systems, encompassing limited gesture vocabulary, contextual understanding, variations in image quality, generalization capabilities, and accessibility considerations. The system's design and development have incorporated innovative solutions to mitigate these limitations, resulting in enhanced overall performance and usability.

The achievements of this sign language recognition system represent a noteworthy advancement in assistive technology for individuals with hearing impairments. By offering a dependable and accurate method of interpreting sign language gestures, the system fosters inclusivity and empowers individuals to communicate effectively in diverse contexts. Its potential benefits encompass enhanced educational experiences, increased employment prospects, and enriched social interactions for individuals who rely on sign language as their primary means of communication.

5.2. LIMITATIONS OF THE PROJECT

i. Limited Gesture Vocabulary:

The system is limited to recognizing and interpreting alphabets in sign language. It does not encompass a broader range of sign language gestures, including words, phrases, or complex grammatical structures. This limitation restricts the system's usability to primarily spelling out words rather than enabling full conversations.

ii. Lack of Contextual Understanding:

The system focuses solely on interpreting isolated gestures without considering the context in which they are used. Sign language relies heavily on context, facial expressions, and body movements to convey meaning. Without contextual understanding, the system may encounter challenges in accurately interpreting gestures that have different meanings based on the surrounding conversation or topic.

iii. Limited Generalization:

The system may face difficulties in generalizing to different users, each with their unique signing style, regional dialects, or idiosyncrasies. It might encounter challenges in adapting to individual variations in hand movements, speed, or execution patterns. Training the system with a more diverse dataset and employing techniques like transfer learning or personalized models could help address this limitation.

iv. Dependency on Image Input Format:

The system solely relies on image input format for gesture recognition, which limits its flexibility and applicability in scenarios where live video feeds or continuous motion-based inputs are available. Real-time gesture recognition using video streams or sensor data can provide more dynamic and accurate results. Incorporating additional modalities, such as depth information or motion capture, could enhance the system's performance and usability.

These limitations serve as potential areas for further research and improvement in sign language recognition systems, aiming to overcome challenges related to gesture vocabulary, contextual understanding, adaptability, and real-time performance.

5.3. FUTURE SCOPE OF WORK

The future objective of this research is to develop an advanced sign language detection system capable of accurately recognizing and interpreting a wide range of sign language gestures. This system aims to address challenges associated with variations in hand shapes, orientations, and motion dynamics, ultimately improving communication and inclusivity for individuals with hearing impairments. The future research directions include:

i. Extending the system's capabilities beyond alphabets to recognize common words, phrases, and complex grammatical structures in sign language.

ii. Real-time recognition of sign language gestures, considering variations in hand gestures and environmental factors, to enable seamless and immediate communication.

iii. Optimizing the system for deployment on mobile devices or wearable technology to ensure portable accessibility.

iv. Enhancing the user experience and interface design of the system to promote usability and adoption.

v. Exploring techniques to improve the system's robustness to factors such as lighting conditions, hand occlusions, and background clutter.

vi. Expanding the dataset to include dynamic hand gestures and investigating temporal modelling techniques, such as recurrent neural networks (RNNs), to enhance recognition accuracy.

By pursuing these research directions, the sign language recognition system can evolve into a sophisticated and versatile tool, facilitating effective communication and inclusivity for individuals with hearing impairments.

5.4. CONCLUSION

The system achieved an impressive accuracy of 96% on the Sign Language MNIST dataset obtained from Kaggle. By leveraging a large dataset of hand gesture images, the system successfully recognized and classified a wide range of sign language alphabets.

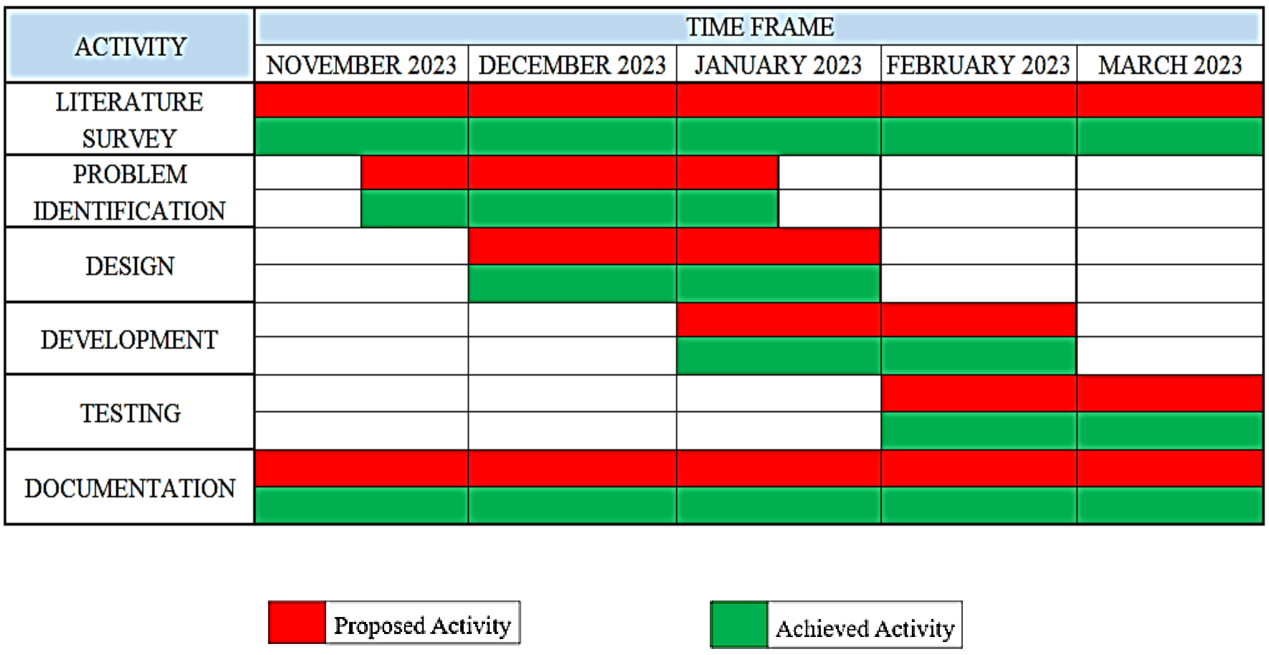
To ensure optimal performance, hyperparameter tuning was conducted to identify the best possible model configuration. This process involved fine-tuning various parameters such as filters, filter size, number of convolution and max pooling pairs, dropout, and data augmentation. The rigorous optimization efforts resulted in a highly efficient and accurate model, capable of accurately interpreting sign language gestures with a 96% recognition accuracy.

It is worth noting that the exclusion of the 'j' and 'z' alphabets due to their motion requirements was a necessary consideration. As this particular dataset consists of static hand gesture images, focusing on static alphabets ensured consistency and reliability in the recognition process.

The successful implementation of this sign language recognition system holds immense potential in various applications. It can serve as an assistive technology for individuals with hearing impairments, enabling effective communication and fostering inclusivity. Furthermore, it can find applications in educational settings, where it can facilitate the learning process for individuals interested in sign language.

Overall, this sign language recognition system represents a significant advancement in the field, offering a reliable and efficient solution for interpreting sign language gestures. It showcases the potential of deep learning approaches in empowering individuals with hearing impairments, promoting communication accessibility, and fostering inclusivity in various domains.

6. GANTT CHART



ACTIVITY	TIME FRAME				
	NOVEMBER 2023	DECEMBER 2023	JANUARY 2023	FEBRUARY 2023	MARCH 2023
LITERATURE SURVEY	🟥	🟥	🟥	🟥	🟥
	🟩	🟩	🟩	🟩	🟩
PROBLEM IDENTIFICATION	🟥	🟥	🟥		
	🟩	🟩	🟩		
DESIGN		🟥	🟥		
		🟩	🟩		
DEVELOPMENT			🟥	🟥	
			🟩	🟩	
TESTING				🟥	🟥
				🟩	🟩
DOCUMENTATION	🟥	🟥	🟥	🟥	🟥
	🟩	🟩	🟩	🟩	🟩

🟥 Proposed Activity

🟩 Achieved Activity

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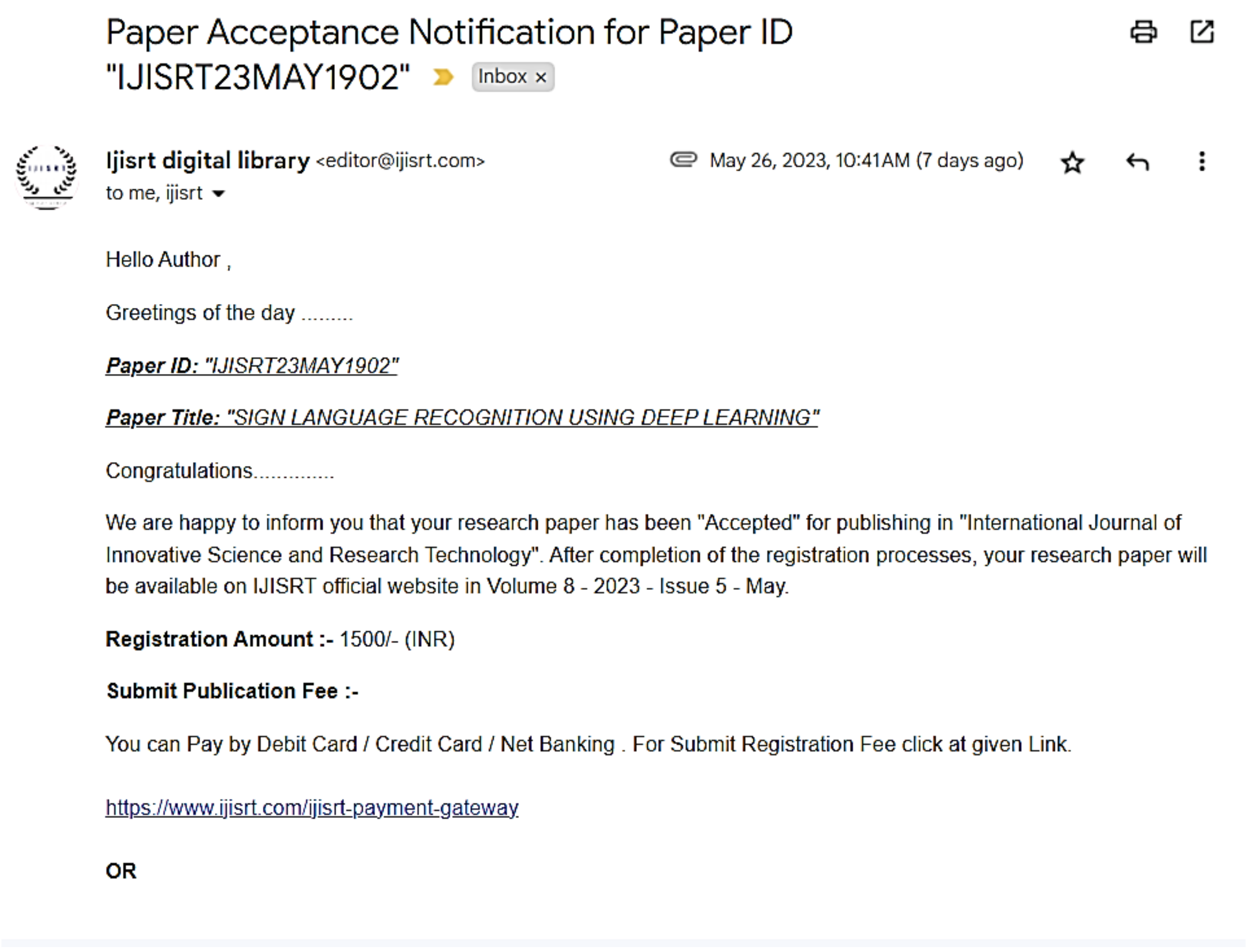
8. ACCEPTANCE LETTER



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