

Smart Vial Detection: With Chatbot Integration

Group – 5

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Introduction

In the pharmaceutical industry, ensuring the quality of vials is essential to maintaining the safety and efficacy of medications and vaccines. However, traditional methods of vial quality assessment often involve manual inspection, which can be time-consuming, subjective, and prone to errors. To address these challenges, we have developed an automated system for vial quality assessment using Convolutional Neural Networks (CNNs) and integrated it with a live production status chatbot. This report provides a detailed overview of the methodology, implementation, and future enhancements of our project.

2. Vial Quality Assessment

2.1. Problem Statement:

The assessment of vial quality is a critical task in pharmaceutical manufacturing to ensure that products meet regulatory standards and are safe for use by patients.

2.2. Solution Approach:

Our approach involved training a CNN model using a diverse dataset of vial images to classify them as either "Good Piece" or "Reject Piece". We utilized TensorFlow and Keras for model development and implemented various image preprocessing techniques to enhance model performance.





2.3. Implementation Details:

Image Preprocessing:

We applied techniques such as rescaling, augmentation, and normalization to ensure consistent and reliable input data for the CNN model.

```
datagen = ImageDataGenerator(  
    rescale=1. / 255,  
    shear_range=0.2,  
    zoom_range=0.2,  
    rotation_range=20,  
    width_shift_range=0.2,  
    height_shift_range=0.2,  
    horizontal_flip=True)
```

Model Architecture:

The CNN model consisted of convolutional layers, max-pooling layers, and dense layers, followed by softmax activation for classification.

```
cnn = tf.keras.models.Sequential()  
cnn.add(tf.keras.layers.Conv2D(filters=32, kernel_size=3,activation='relu',input_shape=[150,150,3]))  
cnn.add(tf.keras.layers.MaxPool2D(pool_size=2, strides=2))  
cnn.add(tf.keras.layers.Conv2D(filters=32, kernel_size=3,activation='relu'))  
cnn.add(tf.keras.layers.MaxPool2D(pool_size=2, strides=2))  
cnn.add(tf.keras.layers.Conv2D(filters=32, kernel_size=3,activation='relu'))  
cnn.add(tf.keras.layers.MaxPool2D(pool_size=2, strides=2))  
cnn.add(tf.keras.layers.Flatten())  
cnn.add(tf.keras.layers.Dense(units=128,activation='relu'))  
cnn.add(tf.keras.layers.Dense(units=1,activation='sigmoid'))  
cnn.compile(optimizer='adam',loss='binary_crossentropy',metrics=['accuracy'])  
cnn.fit(x=training_set,validation_data=test_set,epochs=50)  
test_image= image.load_img('C://Users//syednas2//Downloads//Project//Validation//Good Piece/Screenshot 2024-04-09 080115.png',target_size=(150,150))  
test_image = image.img_to_array(test_image)  
test_image = np.expand_dims(test_image,axis=0)  
result = cnn.predict(test_image/255.0)  
training_set.class_indices  
if result[0][0]> 0.5:  
    prediction = 'Reject Piece'  
else:  
    prediction = 'Good Piece'  
print(prediction)
```

Training Process:

The model was trained using the Adam optimizer and binary cross-entropy loss function for 50 epochs on a curated dataset of vial images.

After 50 epochs, the model achieves a validation accuracy of around 83%.

```

7/7 [=====] - 2s 221ms/step - loss: 0.6025 - accuracy: 0.6857 - val_loss: 0.5825 - val_accuracy: 0.6857
Epoch 41/50
7/7 [=====] - 2s 232ms/step - loss: 0.6211 - accuracy: 0.6436 - val_loss: 0.5253 - val_accuracy: 0.6667
Epoch 42/50
7/7 [=====] - 2s 230ms/step - loss: 0.5811 - accuracy: 0.6733 - val_loss: 0.5089 - val_accuracy: 0.7500
Epoch 43/50
7/7 [=====] - 2s 241ms/step - loss: 0.5737 - accuracy: 0.6733 - val_loss: 0.5087 - val_accuracy: 0.7500
Epoch 44/50
7/7 [=====] - 1s 207ms/step - loss: 0.6132 - accuracy: 0.6436 - val_loss: 0.4868 - val_accuracy: 0.8333
Epoch 45/50
7/7 [=====] - 1s 177ms/step - loss: 0.5688 - accuracy: 0.7228 - val_loss: 0.5126 - val_accuracy: 0.8333
Epoch 46/50
7/7 [=====] - 1s 176ms/step - loss: 0.6172 - accuracy: 0.6733 - val_loss: 0.5297 - val_accuracy: 0.7500
Epoch 47/50
7/7 [=====] - 1s 189ms/step - loss: 0.5932 - accuracy: 0.7030 - val_loss: 0.5050 - val_accuracy: 0.6667
Epoch 48/50
7/7 [=====] - 2s 230ms/step - loss: 0.5921 - accuracy: 0.6733 - val_loss: 0.4853 - val_accuracy: 0.7500
Epoch 49/50
7/7 [=====] - 2s 244ms/step - loss: 0.5967 - accuracy: 0.6535 - val_loss: 0.5075 - val_accuracy: 0.7500
Epoch 50/50
7/7 [=====] - 2s 251ms/step - loss: 0.5247 - accuracy: 0.7525 - val_loss: 0.5136 - val_accuracy: 0.8333
1/1 [=====] - 0s 93ms/step
Good Piece

```

3. Production Status Chatbot

3.1. Introduction:

In addition to vial quality assessment, we developed a chatbot capable of providing live updates on production status, enhancing transparency and communication in the manufacturing process.

3.2. Solution Approach:

Chatbot Development:

The chatbot was built using Python and integrated with the trained CNN model to provide real-time updates on vial quality. It utilizes a tokenizer and label encoder to process user inputs and provide relevant responses.

```

def chat():
    # Load trained model
    model = keras.models.load_model('chat_model')

    # Load tokenizer object
    with open('tokenizer.pickle', 'rb') as handle:
        tokenizer = pickle.load(handle)

    # Load label encoder object
    with open('label_encoder.pickle', 'rb') as enc:
        lbl_encoder = pickle.load(enc)

```

User Interaction:

The chatbot's conversational interface was designed to be intuitive and user-friendly, allowing stakeholders to easily interact with it using natural language.

```

# parameters
max_len = 20

while True:
    print(Fore.LIGHTBLUE_EX + "User: " + Style.RESET_ALL, end="")
    inp = input()
    if inp.lower() == "quit":
        break

    result = model.predict(keras.preprocessing.sequence.pad_sequences(tokenizer.texts_to_sequences([inp]),
                                                                    truncating='post', maxlen=max_len))
    tag = lbl_encoder.inverse_transform([np.argmax(result)])

    for i in data['intents']:
        if i['tag'] == tag:
            print(Fore.GREEN + "ChatBot:" + Style.RESET_ALL , np.random.choice(i['responses']))

    # print(Fore.GREEN + "ChatBot:" + Style.RESET_ALL, random.choice(responses))

print(Fore.YELLOW + "Start messaging with the bot (type quit to stop)!" + Style.RESET_ALL)
chat()

```

3.3. Implementation Details:

Integration:

The chatbot was seamlessly integrated with the vial quality assessment system, allowing users to query production status and receive immediate responses.

```

4/4 [=====] - 0s 4ms/step - loss: 0.1009 - accuracy: 0.9821
Epoch 494/500
2/2 [=====] - 0s 14ms/step - loss: 0.1061 - accuracy: 0.9821
Epoch 495/500
2/2 [=====] - 0s 10ms/step - loss: 0.1053 - accuracy: 0.9821
Epoch 496/500
2/2 [=====] - 0s 15ms/step - loss: 0.1044 - accuracy: 0.9821
Epoch 497/500
2/2 [=====] - 0s 65ms/step - loss: 0.1037 - accuracy: 0.9821
Epoch 498/500
2/2 [=====] - 0s 12ms/step - loss: 0.1031 - accuracy: 0.9821
Epoch 499/500
2/2 [=====] - 0s 13ms/step - loss: 0.1023 - accuracy: 0.9821
Epoch 500/500
2/2 [=====] - 0s 65ms/step - loss: 0.1015 - accuracy: 0.9821

```

Data Retrieval:

Live production status updates were retrieved from a centralized database using API calls, ensuring timely and accurate information delivery to stakeholders.


```

ChatBot: The product is Accepted.
User: Check status of product 002
1/1 [=====] - 0s 48ms/step
ChatBot: The product is Rejected.
User: can you run check on product 002
1/1 [=====] - 0s 48ms/step
ChatBot: Detection camera went down for 0.1245 sec
User: Could you please provide the reason for rejection?
1/1 [=====] - 0s 56ms/step
ChatBot: Defective piece due to high temperature
User: What was the room temperature
1/1 [=====] - 0s 66ms/step
ChatBot: The room temperature was 70°F when detected.
User: Can you run a system check
1/1 [=====] - 0s 71ms/step
ChatBot: Of course! Prod stats are mailed to your system.
User: call assistant
1/1 [=====] - 0s 50ms/step
ChatBot: Dailing in prod call 123456789
User: Check status of product 003
1/1 [=====] - 0s 49ms/step
ChatBot: The product is on belt(Processing).
User: Run a quick check
1/1 [=====] - 0s 54ms/step
ChatBot: .....003 is Accepted and 004 is in initial stage
User: Thank you
1/1 [=====] - 0s 47ms/step
ChatBot: You're most welcome!
User: Bye
1/1 [=====] - 0s 50ms/step
ChatBot: See you later
User: quit

```

4. Future Enhancements

4.1. Video Capturing and Cloud Storage:

We plan to enhance the vial quality assessment system by integrating video capturing capabilities, enabling continuous monitoring of vial quality on the production line. The captured video data will be stored in the cloud for easy access and analysis.

4.2. Real-Time Video Analysis:

The integrated system will be updated to perform real-time video analysis, allowing for automatic detection of defects or abnormalities in vials as they move through the production line.

4.3. Advanced Analytics:

We aim to incorporate advanced analytics techniques such as predictive maintenance and anomaly detection to further improve production efficiency and reduce downtime.

4.4. Scalability and Performance Optimization:

We will focus on optimizing the scalability and performance of the integrated system to handle large volumes of video data and ensure fast and accurate analysis.

4.5 Integrate with cloud:

We had very minimal records generated So using blob storage would have been costly, so we are directly reading the JSON file. On the other side we can push the JSON to cloud and implement a chat bot.

5. Business Implications

5.1. Streamlined Quality Control:

The automated vial quality assessment system reduces manual inspection efforts, ensuring consistent product quality and minimizing the risk of defects.

5.2. Enhanced Decision Making:

The production status chatbot provides stakeholders with real-time updates on production progress, enabling faster decision-making and proactive problem-solving.

5.3. Cost Savings:

By automating manual tasks and improving operational efficiency, the integrated system contributes to cost savings and resource optimization in pharmaceutical manufacturing.

6. Conclusion

The integration of automated vial quality assessment with live production status monitoring represents a significant advancement in pharmaceutical manufacturing processes. With the planned enhancements to incorporate video capturing and cloud-based data analysis, we aim to further improve efficiency, accuracy, and transparency in production operations. We are excited about the potential impact of these enhancements and remain committed to driving innovation in the industry.