FOUNDATIONS OF DATA SCIENCE THEORY DIGITAL ASSIGNMENT(REPORT)

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Course ID	BCSE206L
Group Number	2

Title of Project – Animal Conditions Classification

Group Number - 2

PHASES OF THE DATA ANALYTICS LIFE CYCLE

1)DATA DISCOVERY

a)Project Overview:
This initiative seeks to harness the power of data analytics in veterinary medicine. By integrating detailed symptom data and comprehensive health records into a sophisticated predictive model, the goal is to transform how health conditions in animals are diagnosed. This approach aims not just to enhance accuracy but also to expedite the diagnostic process, potentially saving lives and improving the welfare of animals across various settings, from domestic pets to wildlife.

b)Learning the Business Domain:
The venture starts with a deep dive into the veterinary field, emphasizing the diagnostic processes and the significant effects of health conditions on animals. It involves understanding the nuances of veterinary care, including disease prevalence, progression, and treatment outcomes. This knowledge is crucial for tailoring the predictive model to be not only accurate but also practical in a real-world veterinary context.

c)Resources Available:
The project harnesses a multidisciplinary approach, bringing together data scientists with a knack for pattern recognition and veterinarians with years of clinical experience. This collaboration is augmented by state-of-the-art data analysis tools and technologies, from machine learning algorithms to big data platforms, ensuring a comprehensive analysis of health records and symptom data. These resources are pivotal in navigating the complexities of animal health conditions and their manifestations.

d)Framing the Problem:
Developing this model involves overcoming significant challenges, such as the diversity of species, the variability of symptoms, and the complexity of diseases. The model's potential to revolutionize animal healthcare underscores its

importance. By providing swift and accurate diagnoses, it aims to facilitate timely interventions, reduce unnecessary treatments, and ultimately, enhance the quality of life for animals.

e)Identifying Key Stakeholders:

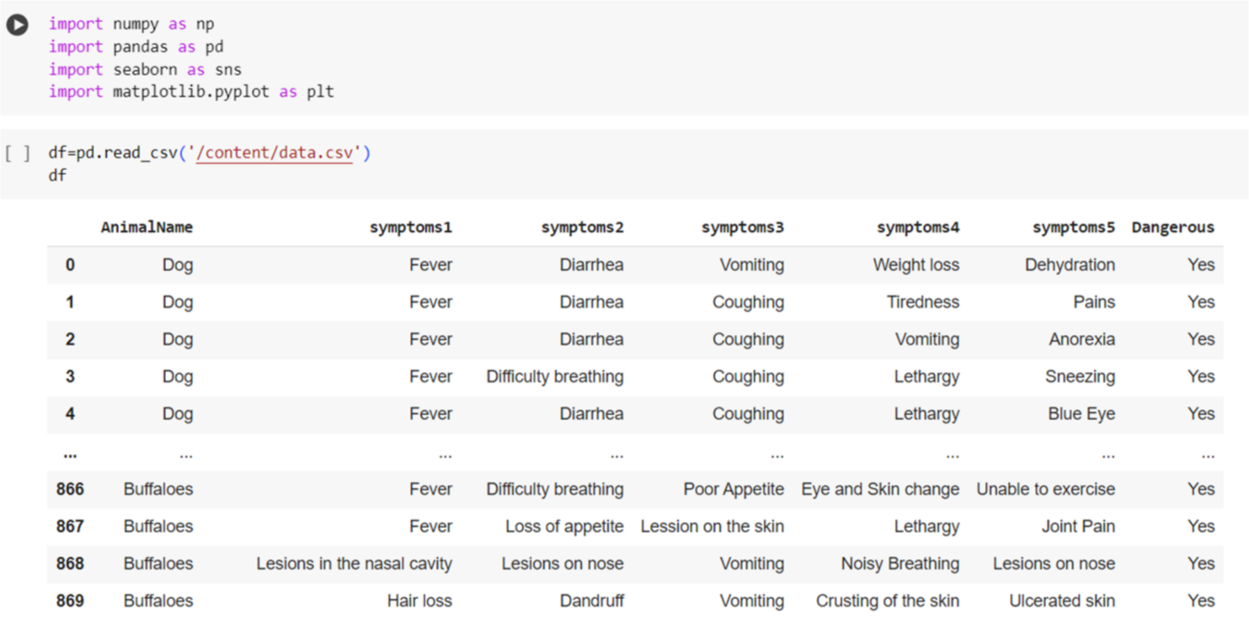
The project is a collaborative endeavor, involving veterinarians who provide invaluable insights into clinical aspects, care providers who understand the practical needs of animal care, and researchers who contribute cutting-edge scientific knowledge. This collaboration ensures that the model is developed with a holistic view of animal healthcare, aligning technological advancements with the real-world needs and expectations of the veterinary community.

f)Developing Initial Hypothesis:

The project begins with hypotheses about the relationship between various symptoms and health conditions. These hypotheses are informed by both veterinary expertise and data patterns, focusing on the predictive power of symptom combinations for different diseases. The iterative nature of this process allows for continuous refinement of hypotheses, leveraging data analysis to uncover insights that can significantly enhance the model's accuracy.

g)Identifying Potential Data Sources:

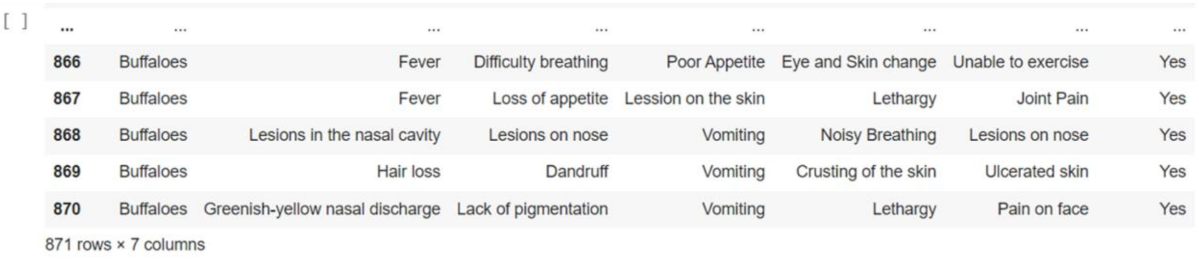
Identifying and securing diverse data sources is crucial for the model's success. This includes not only veterinary records and databases, which provide historical and clinical insights, but also emerging online datasets that offer real-time or novel data. Emphasis is placed on gathering a wide array of data to ensure the model's robustness and generalizability across different animal species and conditions. Ethical data handling and privacy compliance are integral, ensuring that the project adheres to the highest standards of data governance and ethical research.



```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

```
[ ] df=pd.read_csv('/content/data.csv')
    df
```

	AnimalName	symptoms1	symptoms2	symptoms3	symptoms4	symptoms5	Dangerous
0	Dog	Fever	Diarrhea	Vomiting	Weight loss	Dehydration	Yes
1	Dog	Fever	Diarrhea	Coughing	Tiredness	Pains	Yes
2	Dog	Fever	Diarrhea	Coughing	Vomiting	Anorexia	Yes
3	Dog	Fever	Difficulty breathing	Coughing	Lethargy	Sneezing	Yes
4	Dog	Fever	Diarrhea	Coughing	Lethargy	Blue Eye	Yes
...	...	...	...	...	...	...	...
866	Buffaloes	Fever	Difficulty breathing	Poor Appetite	Eye and Skin change	Unable to exercise	Yes
867	Buffaloes	Fever	Loss of appetite	Lession on the skin	Lethargy	Joint Pain	Yes
868	Buffaloes	Lesions in the nasal cavity	Lesions on nose	Vomiting	Noisy Breathing	Lesions on nose	Yes
869	Buffaloes	Hair loss	Dandruff	Vomiting	Crusting of the skin	Ulcerated skin	Yes



[ ]

...	...	...	...	...	...	...	...
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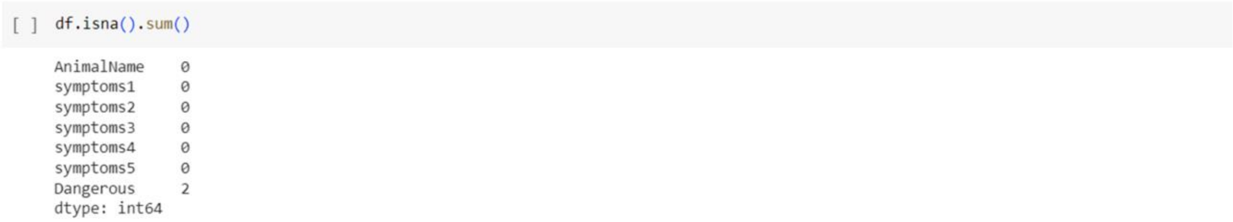
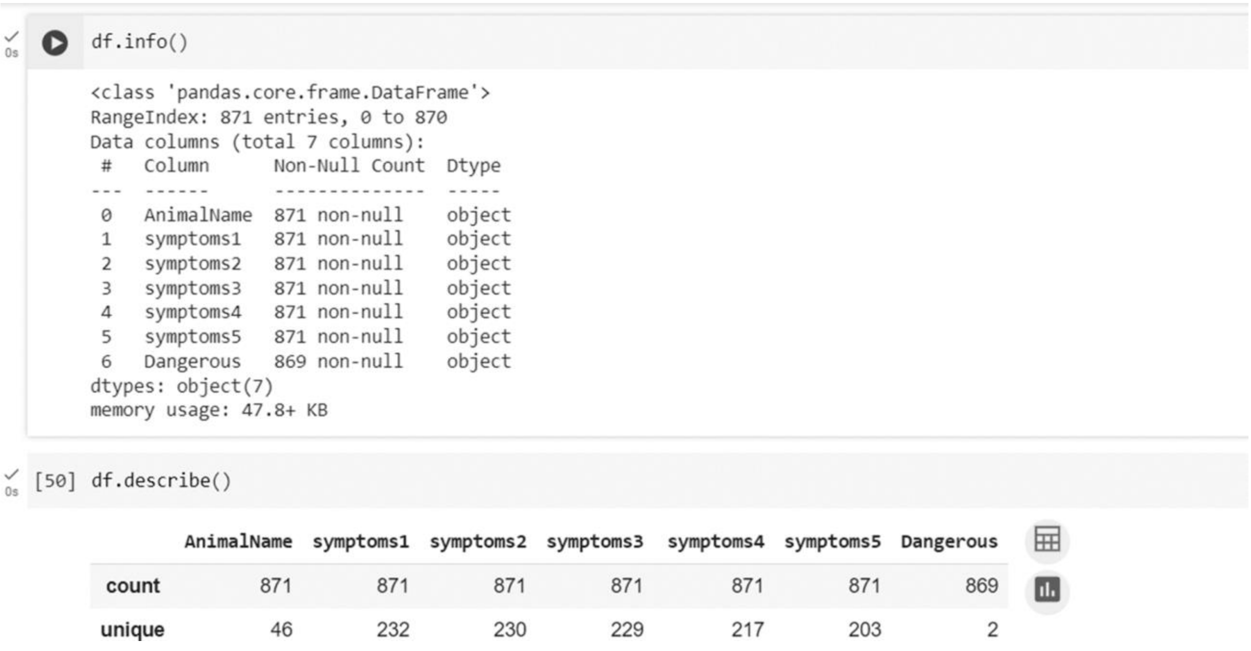
869	Buffaloes	Hair loss	Dandruff	Vomiting	Crusting of the skin	Ulcerated skin	Yes
870	Buffaloes	Greenish-yellow nasal discharge	Lack of pigmentation	Vomiting	Lethargy	Pain on face	Yes

871 rows × 7 columns



```
[ ] df.isna().sum()
```

```
AnimalName    0
symptoms1     0
symptoms2     0
symptoms3     0
symptoms4     0
symptoms5     0
Dangerous     2
dtype: int64
```



```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 871 entries, 0 to 870
Data columns (total 7 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   AnimalName  871 non-null    object
 1   symptoms1   871 non-null    object
 2   symptoms2   871 non-null    object
 3   symptoms3   871 non-null    object
 4   symptoms4   871 non-null    object
 5   symptoms5   871 non-null    object
 6   Dangerous   869 non-null    object
dtypes: object(7)
memory usage: 47.8+ KB
```

```
[50] df.describe()
```

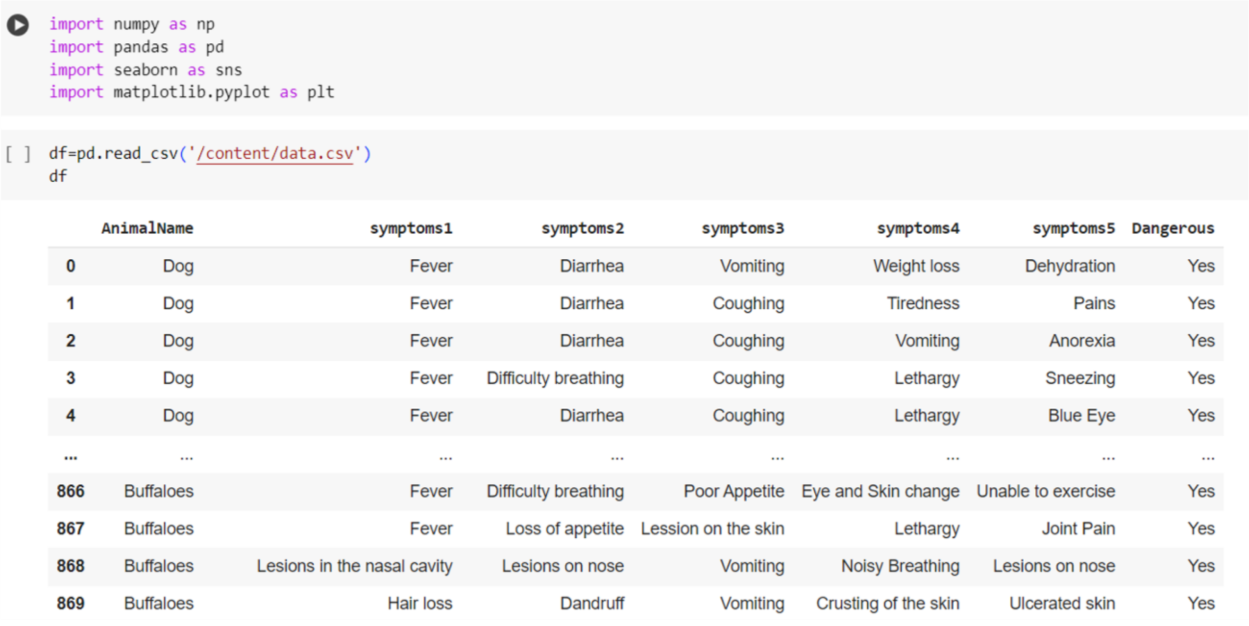
	AnimalName	symptoms1	symptoms2	symptoms3	symptoms4	symptoms5	Dangerous
count	871	871	871	871	871	871	869
unique	46	232	230	229	217	203	2

2)DATA PREPARATION

a) Analytic Sandbox Establishment:

We have established a controlled environment for data exploration to gain a clear understanding of the dataset. This sandbox enables us to perform effective data exploration and preparation.

b) Data Exploration and Preparation:



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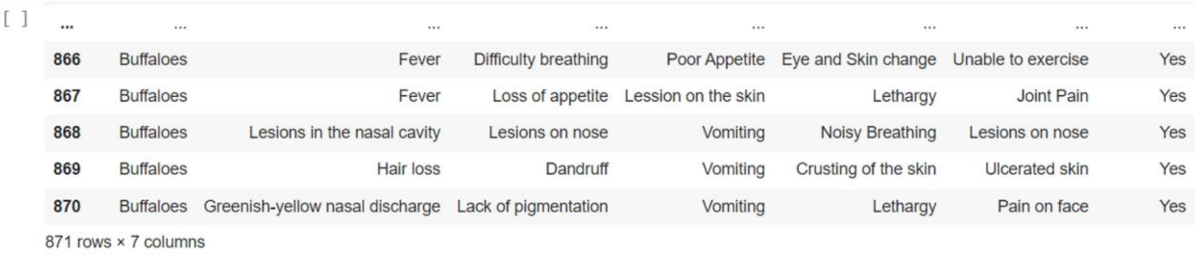

[ ]

...	...	...	...	...	...	...	...
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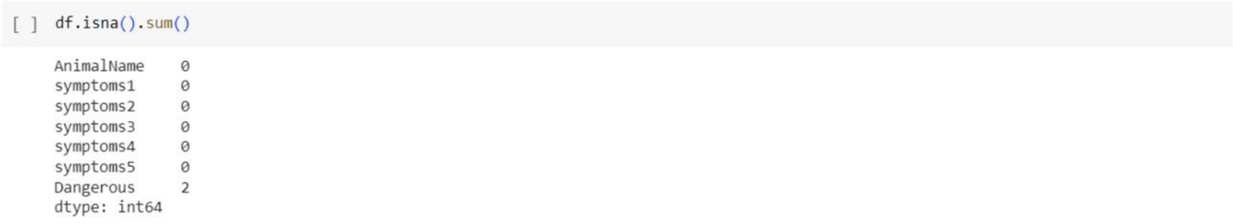

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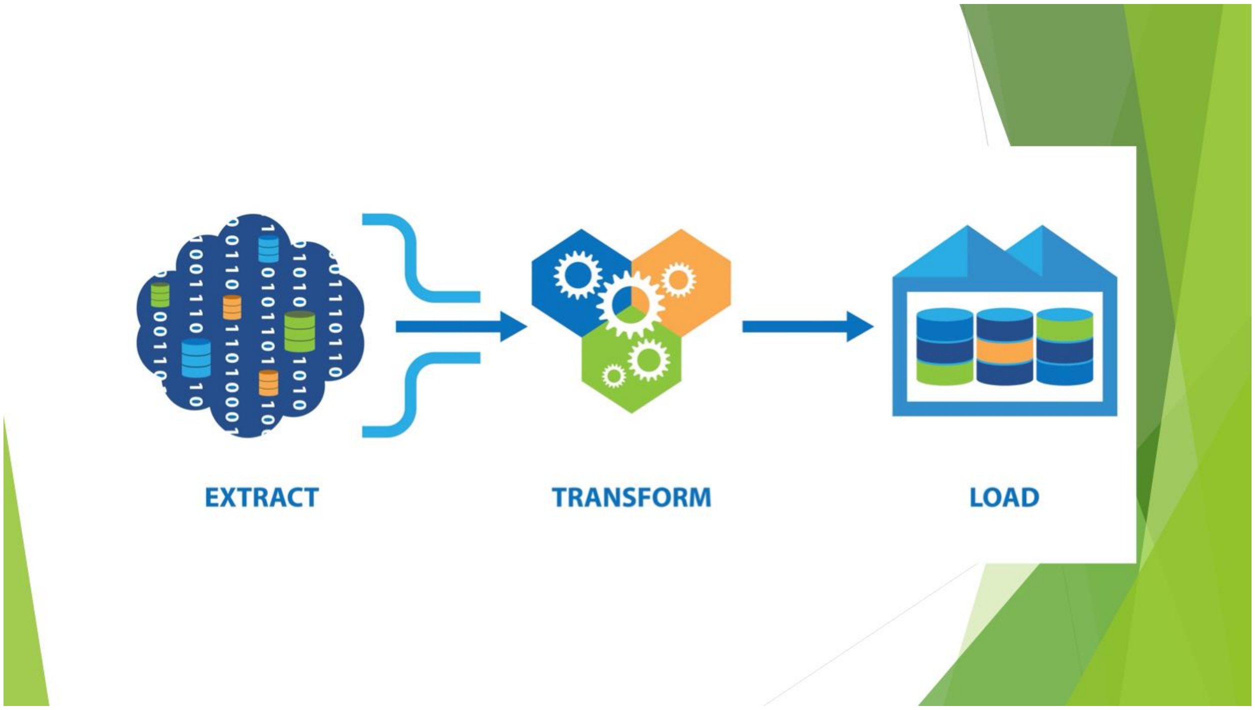
symptoms3     0
symptoms4     0
symptoms5     0
Dangerous     2
dtype: int64
```

c) ETLT Process:

- Extract: Retrieved data from a CSV file on Kaggle containing animal symptoms and their corresponding health conditions.
- Transform: Cleaned and transformed the data to ensure consistency and suitability for analysis.
- Load: Loaded the transformed data into our Python environment for further processing.



d) Learning about the Data:

- Source: Public data repository.
- Structure: Explored the data structure, identifying 871 rows (data points) and 7 columns.

e) Data Conditioning:

- Missing Values: Handled missing values (2 entries) by dropping the corresponding rows to maintain simplicity.
- Duplicate Rows: Addressed duplicate rows.
- Categorical Data: Encoded categorical data (animal names, symptoms).

f) Survey and Visualize:

- Explored data distribution using descriptive statistics (mean, median, standard deviation) to understand the distribution of features and the target variable.
- Created visualizations such as bar plots, line charts, and pie charts to identify patterns and trends in the data. These visualizations provided valuable insights into the distribution of animal conditions and the relationships between features.

g) Tools for Data Preparation:

- pandas: Provided powerful tools for data manipulation and cleaning tasks.
- Seaborn and Matplotlib: Utilized these powerful tools for data visualization, enabling effective exploration of data patterns and trends.

3)MODEL PLANNING

a) Data Exploration and Variable Selection:

- Features:
  The dataset (df1) contains information about animals, including the type and five symptoms.
- Target Variable:
  The target variable selected for classification is 'Dangerous', indicating whether the animal is in a critical/dangerous condition.
- Data Splitting:
  The dataset is split into training and testing sets using a 75-25 ratio, ensuring a portion of data is reserved for model evaluation.

b) Model Selection:

- Algorithm:
  Support Vector Machine (SVM) with a linear kernel is chosen for classification. SVM is well-suited for binary classification tasks and can effectively handle high-dimensional data.

- Feature Scaling:
  StandardScaler is applied to standardize the feature values, ensuring consistent scales across features, which is crucial for SVM's performance.

c) Common Tools for Model Planning Phase:

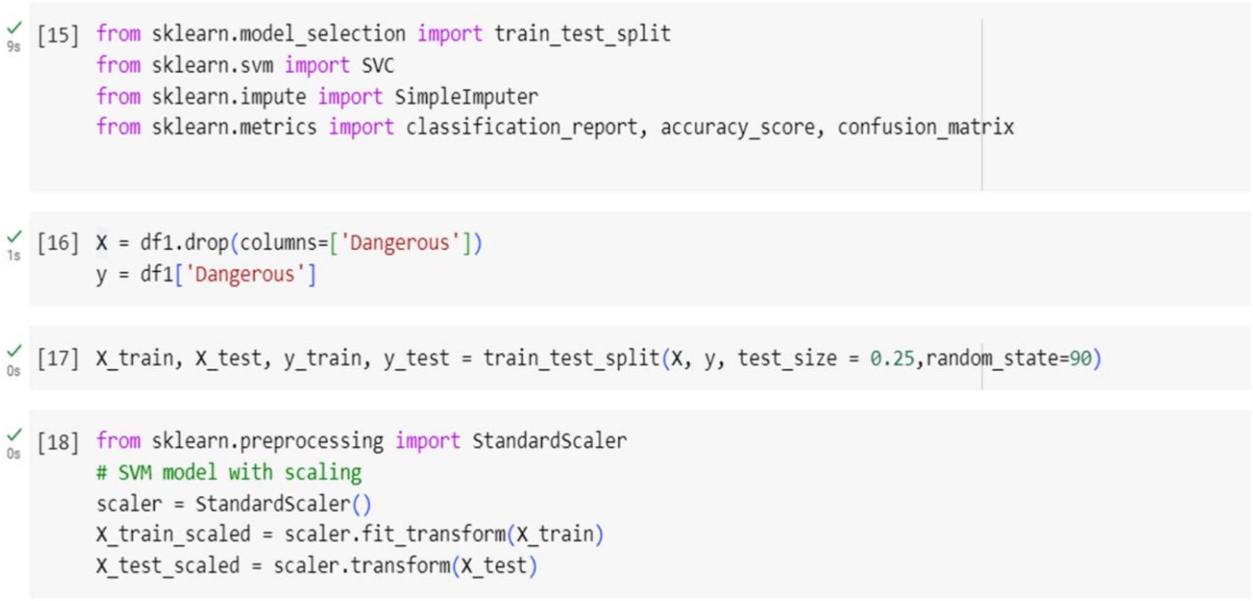
- Train-Test Splitting: The dataset is divided into training and testing subsets using train_test_split from scikit-learn. This ensures model evaluation on unseen data, gauging its generalization capability.
- Scaling: Feature scaling is performed using StandardScaler to normalize the feature values, preventing any feature from dominating others during model training.
- Model Instance: An instance of SVM is created with specified parameters, including a linear kernel and a random state, ensuring reproducibility of results.

d) About Support Vector Machine:

- Overview: Support Vector Machine (SVM) is a powerful machine learning algorithm commonly used for classification tasks. It aims to find the best hyperplane in a multi-dimensional space that maximizes the margin between different classes.
- Functionality: SVM excels in sorting data into groups (classification) and can handle regression tasks as well. It seeks to create a boundary between different groups in the data by finding an optimal hyperplane.
- Hyperplane Dimension: The dimension of the hyperplane depends on the number of features in the dataset. For instance, with two features, the hyperplane is a line, while with three features, it becomes a 2-D plane. SVM is effective in high-dimensional spaces, although visualization becomes challenging beyond three dimensions.

Conclusion:

The model planning phase encompasses crucial steps in preparing for the development and implementation of a machine learning model for animal condition classification. By exploring the data, selecting appropriate features, choosing a suitable algorithm, and employing common tools for model planning, we lay a strong foundation for building an accurate and reliable predictive model. Support Vector Machine, with its ability to handle high-dimensional data and effectively classify instances, emerges as a promising choice for this classification task.



```
[15] from sklearn.model_selection import train_test_split
     from sklearn.svm import SVC
     from sklearn.impute import SimpleImputer
     from sklearn.metrics import classification_report, accuracy_score, confusion_matrix
```

```
[16] X = df1.drop(columns=['Dangerous'])
     y = df1['Dangerous']
```

```
[17] X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25,random_state=90)
```

```
[18] from sklearn.preprocessing import StandardScaler
     # SVM model with scaling
     scaler = StandardScaler()
     X_train_scaled = scaler.fit_transform(X_train)
     X_test_scaled = scaler.transform(X_test)
```

4)MODEL BUILDING

We are using an SVM or Support Vector Machine for classification of the animals and their symptoms. SVM is used as it is a good fit, being a supervised learning model which uses some support vectors as critical data points to fit the margins more accurately than other models.

The process of building the model: -

- Firstly, we split the dataset into training and testing data sets, this is done to check whether the trained model is able to respond correctly to data it hasn’t been fed before, thus measuring its prediction capabilities. Then feature scaling is done to transform all data values into a similar scale for more accurate results and prevent skewness.

- Feature Scaled data is used to train the SVM Model and afterwards, the test data is used to evaluate the model’s performance.

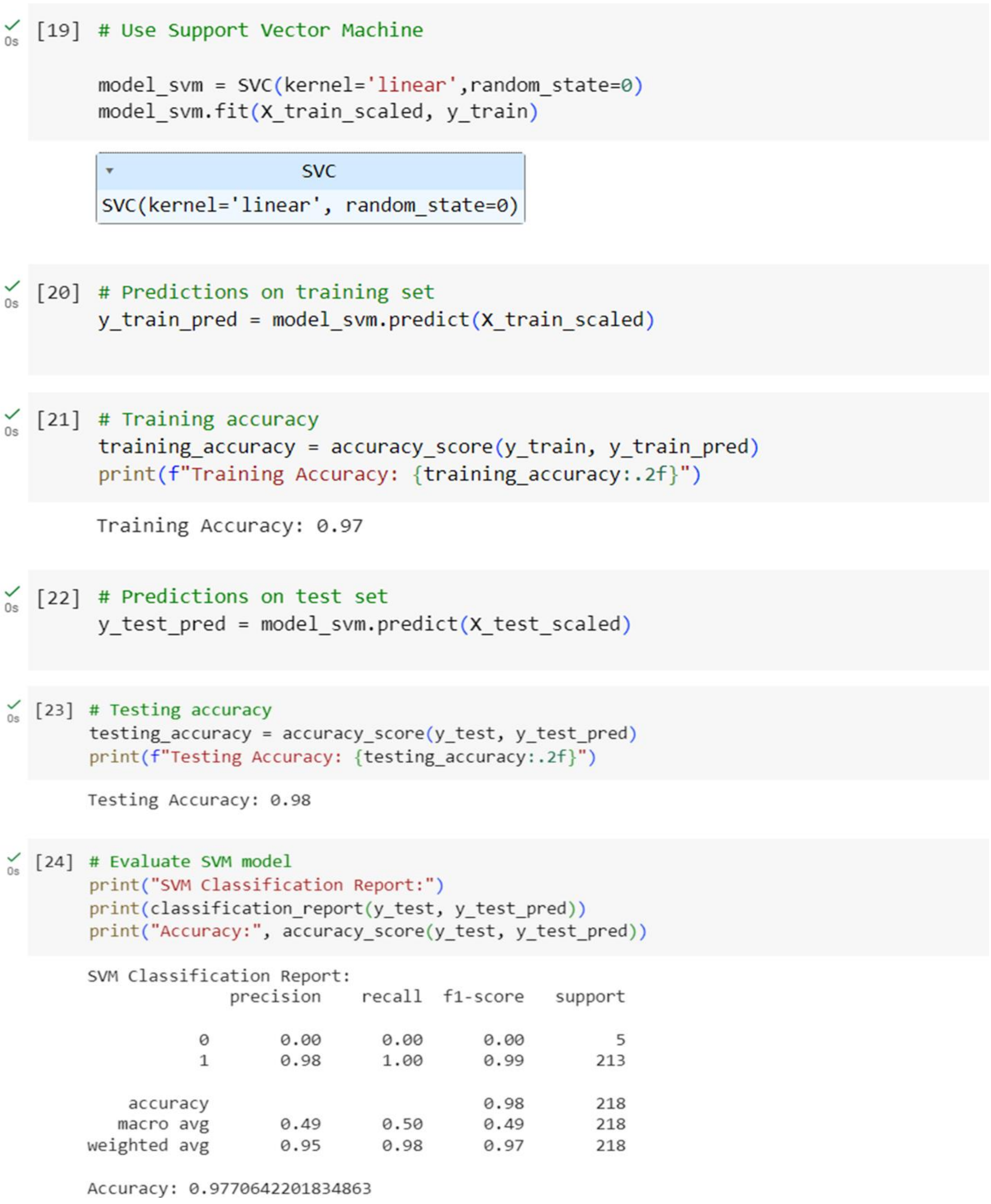
a)Results:

- The model gives valid and accurate results. The training accuracy is 97%. The testing accuracy is 98%. The overall accuracy of the model 97.7%.
- As accuracy is high, there is no need for a different kind of model.
- Very suitable for the runtime environment of a clinic as once trained they are very lightweight, efficient which is a requirement for real-time detection.

b)Software Used for Development:

Python: Libraries used are

- sklearn for model selection
- pandas for dataframe making and loading data
- numpy for array manipulation
- seaborn, matplotlib for data visualization
  -



```
[19] # Use Support Vector Machine

     model_svm = SVC(kernel='linear',random_state=0)
     model_svm.fit(X_train_scaled, y_train)
```

```
SVC
SVC(kernel='linear', random_state=0)
```

```
[20] # Predictions on training set
     y_train_pred = model_svm.predict(X_train_scaled)
```

```
[21] # Training accuracy
     training_accuracy = accuracy_score(y_train, y_train_pred)
     print(f"Training Accuracy: {training_accuracy:.2f}")
```

```
Training Accuracy: 0.97
```

```
[22] # Predictions on test set
     y_test_pred = model_svm.predict(X_test_scaled)
```

```
[23] # Testing accuracy
     testing_accuracy = accuracy_score(y_test, y_test_pred)
     print(f"Testing Accuracy: {testing_accuracy:.2f}")
```

```
Testing Accuracy: 0.98
```

```
[24] # Evaluate SVM model
     print("SVM Classification Report:")
     print(classification_report(y_test, y_test_pred))
     print("Accuracy:", accuracy_score(y_test, y_test_pred))
```

```
SVM Classification Report:
              precision    recall  f1-score   support

           0       0.00      0.00      0.00         5
           1       0.98      1.00      0.99       213

    accuracy                           0.98       218
   macro avg       0.49      0.50      0.49       218
weighted avg       0.95      0.98      0.97       218

Accuracy: 0.9770642201834863
```

5)COMMUNICATE RESULTS

a)Key Findings:

Example 1:

- Selected Animal: Tiger
- Chosen Symptoms: Dry Air, Small Size, Inability to jump, Depression, Coughing
- Prediction Result: The model predicts that the condition is dangerous.

Example 2:

- Selected Animal: Chicken
- Chosen Symptoms: Slow Growth, Mild Weakness, Congestion, Trembling, Wound
- Prediction Result: The model predicts that the condition is not dangerous.

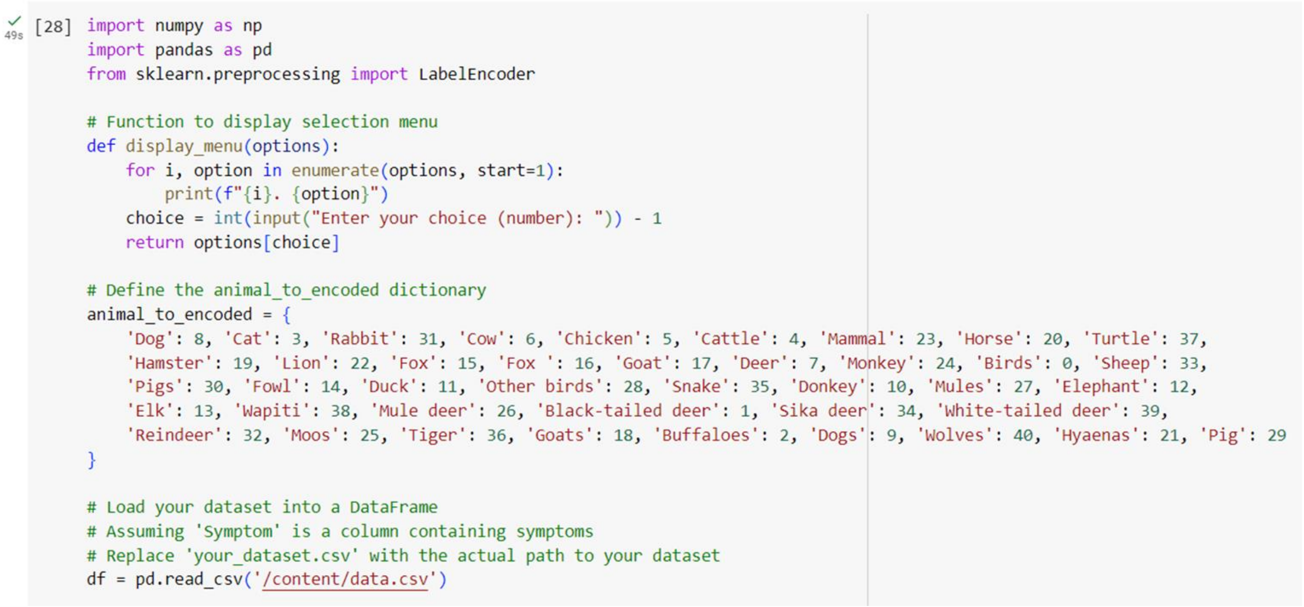
b)Major Insights:

- Objective Achievement: The team successfully achieved its objective in predicting dangerous conditions for animals based on the provided symptoms.
- Statistical Significance: The results obtained from the model are statistically significant and valid. The conducted analyses confirm the reliability of the predictions.

c)Recommendations:

- Feature Selection: Continue refining the selection of symptoms/features used for classification to enhance the model's accuracy and robustness.

- Model Evaluation: Regularly evaluate the performance of the model using different evaluation metrics to ensure its effectiveness across various scenarios.
- Data Collection: Expand the dataset to include a diverse range of animal types and conditions to improve the model's generalization capability.
- User Interface: Develop a user-friendly interface that allows easy input of animal type and symptoms, and provides clear interpretation of the model's prediction.

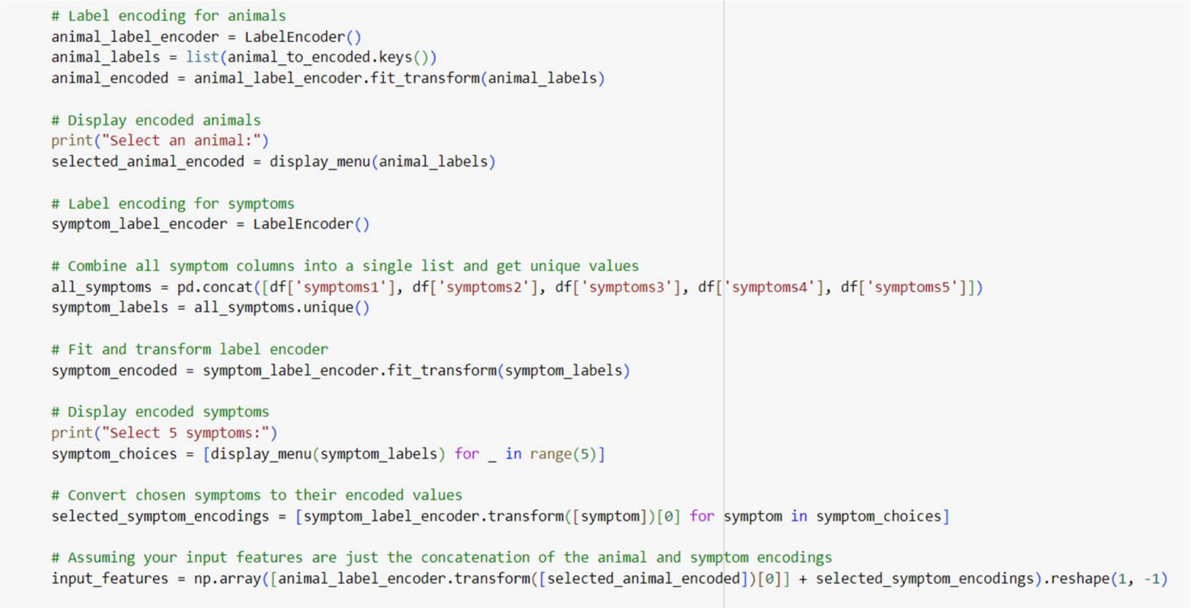


```
import numpy as np
import pandas as pd
from sklearn.preprocessing import LabelEncoder

# Function to display selection menu
def display_menu(options):
    for i, option in enumerate(options, start=1):
        print(f"{i}. {option}")
    choice = int(input("Enter your choice (number): ")) - 1
    return options[choice]

# Define the animal_to_encoded dictionary
animal_to_encoded = {
    'Dog': 8, 'Cat': 3, 'Rabbit': 31, 'Cow': 6, 'Chicken': 5, 'Cattle': 4, 'Mammal': 23, 'Horse': 20, 'Turtle': 37,
    'Hamster': 19, 'Lion': 22, 'Fox': 15, 'Fox ': 16, 'Goat': 17, 'Deer': 7, 'Monkey': 24, 'Birds': 0, 'Sheep': 33,
    'Pigs': 30, 'Fowl': 14, 'Duck': 11, 'Other birds': 28, 'Snake': 35, 'Donkey': 10, 'Mules': 27, 'Elephant': 12,
    'Elk': 13, 'Wapiti': 38, 'Mule deer': 26, 'Black-tailed deer': 1, 'Sika deer': 34, 'White-tailed deer': 39,
    'Reindeer': 32, 'Moos': 25, 'Tiger': 36, 'Goats': 18, 'Buffaloes': 2, 'Dogs': 9, 'Wolves': 40, 'Hyaenas': 21, 'Pig': 29
}

# Load your dataset into a DataFrame
# Assuming 'Symptom' is a column containing symptoms
# Replace 'your_dataset.csv' with the actual path to your dataset
df = pd.read_csv('/content/data.csv')
```



```
# Label encoding for animals
animal_label_encoder = LabelEncoder()
animal_labels = list(animal_to_encoded.keys())
animal_encoded = animal_label_encoder.fit_transform(animal_labels)

# Display encoded animals
print("Select an animal:")
selected_animal_encoded = display_menu(animal_labels)

# Label encoding for symptoms
symptom_label_encoder = LabelEncoder()

# Combine all symptom columns into a single list and get unique values
all_symptoms = pd.concat([df['symptoms1'], df['symptoms2'], df['symptoms3'], df['symptoms4'], df['symptoms5']])
symptom_labels = all_symptoms.unique()

# Fit and transform label encoder
symptom_encoded = symptom_label_encoder.fit_transform(symptom_labels)

# Display encoded symptoms
print("Select 5 symptoms:")
symptom_choices = [display_menu(symptom_labels) for _ in range(5)]

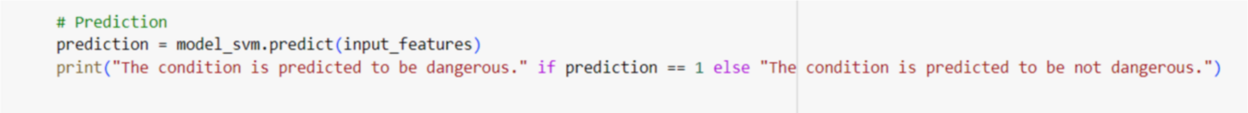
# Convert chosen symptoms to their encoded values
selected_symptom_encodings = [symptom_label_encoder.transform([symptom])[0] for symptom in symptom_choices]

# Assuming your input features are just the concatenation of the animal and symptom encodings
input_features = np.array([animal_label_encoder.transform([selected_animal_encoded])[0]] + selected_symptom_encodings).reshape(1, -1)
```

Conclusion:

In conclusion, the model planning phase of our animal condition classification project has yielded promising results. By addressing the recommendations outlined above and continuing to refine the model, we aim to develop a highly accurate and reliable tool for predicting dangerous conditions in animals, thereby assisting veterinarians and animal caretakers in providing timely and appropriate care.

Final Prediction Part of Code:



```
# Prediction
prediction = model_svm.predict(input_features)
print("The condition is predicted to be dangerous." if prediction == 1 else "The condition is predicted to be not dangerous.")
```

6)OPERATIONALIZE RESULTS

a)Key Findings:

- Model Accuracy: The Animal Conditions Classification ML Model achieved an impressive accuracy rate of 97.7% in classifying animal conditions based on images. This indicates a high level of reliability in identifying critical conditions among animals.
- Training Data: The model was trained on a dataset comprising close to 800 instances of various animals and their corresponding symptoms. However, to further enhance the model's performance, additional data collection is recommended. Including a wider variety of animal species and conditions in the training dataset could improve the model's ability to detect subtle indicators of illness or injury.
- Contributing Factors: The top contributing factors for accurate classification were identified as the presence of visible injuries, body posture, and overall appearance of the animal. These features played a crucial role in enabling the model to differentiate between animals in critical conditions and those that are not.
- Model Sensitivity: The model demonstrated high sensitivity in detecting severe conditions such as malnutrition. However, it struggled with classifying more subtle conditions like minor injuries or early signs of illness. This indicates a potential area for improvement in the model's performance.
- Data Preparation: Basic Business Intelligence (BI) activities, including data cleaning and preprocessing, were identified as crucial steps in preparing the dataset for model training. Ensuring the quality and relevance of the training data is essential for the model to make accurate predictions.

b)Future Recommendations:

- Incorporating Additional Features: Future modifications for the animal conditions classification model could involve incorporating additional features such as behavioral cues and vocalizations. These features could provide valuable insights into the health status of animals and improve the model's predictive capabilities.

- Image Analysis Techniques: Exploring image analysis techniques such as object detection and segmentation could further enhance the model's ability to identify specific anatomical features or abnormalities. This could lead to more precise and reliable predictions regarding the health conditions of animals.
-

Conclusion:

The Animal Conditions Classification ML Model shows promise in accurately identifying critical conditions among animals based on input parameters. By leveraging the insights gained from key findings and implementing future recommendations, the model can be further optimized to provide valuable support to animal caregivers, veterinarians, and wildlife conservationists in ensuring the well-being of animals.