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Deep Learning Based Nutrient-Driven Categorization of Packaged Food Sauces: Enhancing Consumer Awareness through Rule-Based Classification

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Abstract:

Artificial Intelligence is the technique that uses multiple layers of a neural network to automatically distinguish patterns to learn to make predictions. A problem that a human faces on a daily basis is how to make a conscious decision regarding our daily packaged food sauces consumption that is nutritious healthy. By having a tool that helps facilitate the decision making process of what type of food to eat by showing useful nutritional information to us immediately would greatly improve our lives. By critically analysing prominent research papers that relate to Artificial Intelligence techniques to classify food and their nutrients composition, we decided upon the suitable Artificial Intelligence algorithm to classify food nutrients composition as well as the appropriate image dataset to be used. Therefore in this paper we propose the classification of food nutrients composition utilizing Artificial Intelligence techniques. The proposed framework uses Artificial neural networks (ANN) as a basis of recognising images of packaged food sauces and classifying the food into their corresponding nutrients composition such as fats, carbohydrates, proteins and more. Once the nutritional score has been generated, it can be used to help consumers make informed choices about the food they eat. For example, food manufacturers can display the nutritional score on the product label, allowing consumers to easily compare the nutritional value of different sauces. As part of our future work, we shall use the proposed framework to conduct the training and implementation of the Artificial Intelligence model to make predictions on food nutrients. The chosen dataset shall be used to train the model where patterns and characteristics of the food images are distinguished over multiple passes of the neural network. Once the model has been trained, then new food images may be introduced to make a prediction from the context that have been learned from before.

Keywords : Artificial neural networks (ANN), Ml, packaged food,Svm, Classifications, Artificial Intelligence

Introduction:

In contemporary society, the ubiquity of packed food sauces has become a defining feature of modern dietary habits. With the convenience they offer, these sauces have seamlessly integrated into our culinary routines, yet their health implications remain a subject of concern. The rise of lifestyle-related health issues, coupled with an increased awareness of the significance of nutritional choices, has underscored the need for a comprehensive understanding of the health impact of such products. This project endeavors to bridge this knowledge gap by harnessing the power of Artificial Intelligence

(AI) to generate nuanced nutritional scores for various packed food sauces. Our aim is twofold: firstly, to provide consumers with actionable insights into the nutritional profiles of these sauces, empowering them to make informed dietary decisions; and secondly, to offer food manufacturers and policymakers valuable data-driven feedback, aiding in the formulation of healthier product offerings and regulatory measures. The contemporary food landscape is characterized by a myriad of packed food sauces, ranging from classic condiments to complex flavor enhancers. These products often contain a diverse array of ingredients, including preservatives, additives, and flavorings, which can significantly impact their nutritional value. Traditional methods of nutritional analysis are often insufficient to capture the complexity of these sauces, necessitating a more sophisticated approach. In response to this challenge, our project proposes the development of an AI-driven system capable of analyzing the nutritional composition of packed food sauces with unprecedented accuracy and granularity. Leveraging machine learning algorithms and advanced data processing techniques, our system will parse through ingredient lists, nutritional labels, and other relevant data sources to derive comprehensive nutritional scores for each sauce. By employing AI, we seek to overcome the limitations of traditional nutritional analysis methods, which are often time-consuming, labor-intensive, and prone to subjective interpretation. Our approach promises to deliver standardized, objective assessments of packed food sauces, enabling meaningful comparisons across products and brands. Furthermore, our project aligns with broader efforts to promote public health and nutrition literacy. In an era marked by rising rates of obesity, diabetes, and other diet-related diseases, the need for accessible, actionable nutritional information has never been greater. Through our research, we aspire to empower individuals to make healthier food choices, thereby fostering a culture of wellness and vitality. In the following sections, we will delve into the methodology employed in the development of our AI-driven nutritional scoring system, present our findings, and discuss their implications for consumers, food manufacturers, and policymakers alike. Through our collective endeavors, we aim to catalyze positive change in the realm of nutrition, one packed food sauce at a time.

Motivation :

The motivation behind this project stems from the growing concern over the nutritional quality of packed food sauces and their impact on public health. In today's fast-paced world, packed food sauces have become staples in many households, offering convenience and flavor enhancement to a variety of dishes. However, the widespread consumption of these products raises questions about their nutritional value and potential health risks. One of the primary motivations for undertaking this research is the lack of comprehensive information available to consumers regarding the nutritional content of packed food sauces. While nutritional labels provide some basic information, they often fail to capture the full spectrum of ingredients and their potential health implications. This leaves consumers in a dilemma, unsure about the healthiness of the products they consume on a regular basis. Moreover, the increasing prevalence of lifestyle-related health conditions such as obesity, diabetes, and cardiovascular diseases underscores the urgency of addressing dietary factors, including the consumption of processed and packaged foods. Packed food sauces, with their often high levels of sodium, sugar, and unhealthy fats, contribute to the burden of these health issues.

By developing an AI-driven nutritional scoring system specifically tailored for packed food sauces, we aim to fill this gap in knowledge and empower consumers to make more informed dietary choices. Our motivation is rooted in the belief that access to accurate and transparent information about the nutritional quality of food products is essential for promoting healthier eating habits and reducing the incidence of diet-related diseases. Furthermore, this research has broader implications for the food industry and regulatory agencies. By providing insights into the nutritional profiles of packed food sauces, we hope to encourage food manufacturers to reformulate their products to improve their nutritional quality. Additionally, our findings may inform policy decisions related to food labeling and advertising, contributing to a more conducive environment for healthy eating. By generating a nutritional score using AI, we can provide consumers with valuable information about the nutritional content of the sauces they consume and encourage them to make informed choices. Furthermore, food manufacturers can use this information to create healthier alternatives and reduce the risk of diet-related diseases. This study aims to contribute to the promotion of healthier eating habits and improve public health by providing a comprehensive understanding of the nutritional content of packed food sauces.

- Understanding the health impact of packed food sauces using AI-driven nutritional score generation is important for promoting health awareness. With the rise in diet-related diseases, it is crucial to educate and raise awareness

- Among consumers about the nutritional content of the food they consume. Generating a nutritional score using AI provides an easy-to-understand indicator

- Overall nutritional value of packed food sauces. The nutritional score can help consumers make informed choices about the food They eat, and encourage them to select healthier options. The study can have a positive impact on public health by promoting healthier.

- Eating habits and reducing the risk of diet-related diseases. The study can encourage food manufacturers to develop healthier alternatives

- By providing consumers with valuable information about the nutritional content of packed food sauces, and encouraging them to make healthier choices. By reducing the risk of diet-related diseases, the study can improve overall well

In summary, the motivation behind this project lies in the desire to address the pressing need for greater transparency and accountability in the food industry, particularly concerning the nutritional content of packed food sauces. By leveraging the power of AI to analyze and evaluate these products, we aspire to empower consumers, promote public health, and drive positive change in the food ecosystem.

Literature Survey :

Year	Title and authors	Methodology
2023	Food-Nutrition FW: A Novel Framework for the Automatic Synthesis and Analysis of Eating Behaviors	a framework that facilitates the creation of food image datasets tailored to configurable eating behaviours. The framework considers various aspects such as region and lifestyle, simulating a user-friendly scenario where individuals capture food images using their smartphones. The study also presents a novel food image dataset comprising 4,800 diverse weekly diets from 15 distinct profiles, ranging from healthy eating habits to unhealthy ones. Finally, we evaluate the healthy eating behaviours through a score based on the Normalised Mahalanobis Distance (NMD), achieving promising results (99.53% and 99.60% accuracy and sensitivity, respectively).
2022	Applying Image-Based Food Recognition Systems On Dietary Assessment: a Systematic Review	Automatic record keeping approaches that adopt mobile cameras and computer vision methods seem to simplify the process and can improve current human-centric diet monitoring methods. Here we present an extended critical literature overview of image-based food recognition systems (IBFRS) combining a camera of the user's mobile device with computer vision methods and publicly available food datasets (PAFD). In brief, such systems consist of several phases, such as the segmentation of the food items on the plate, the classification of the food items in a specific food category, and the estimation phase of volume, calories or nutrients of each food item
2021	UEC-Food Pix Complete: A Large-Scale Food Image Segmentation Dataset	automatically generated in the previous UEC-FoodPix. As a result, the segmentation performance was much improved compared to the segmentation model trained with the original UEC-FoodPix. In addition, as applications of the new food segmentation dataset, we performed food calorie estimation using the food segmentation models trained with "UEC-FoodPix Complete", and food image synthesis from segmentation masks.
2020	Food Image Recognition Based on Densely Connected Convolutional Neural	techniques for classification,including support vector machine (SVM), artificial neuralnetworks (ANN), and random forest. Convolutional NeuralNetworks (CNN)

	Networks	have demonstrated high efficiency and ef-fectiveness in feature extraction from images and are suitablefor food recognition. However, the training of a reasonableCNN model may require millions of images

Methodology:

Data Collection:

Data on packed food sauces and their nutritional information will be collected from various sources such as food product databases, nutritional labels, and ingredient lists. Criteria for selection include the types of sauces considered and the timeframe of data collection.

Data Pre-processing:

The collected data will undergo preprocessing steps including cleaning, handling missing values, and standardization to prepare it for analysis.

Feature Extraction:

Features such as nutritional components (e.g., calories, fat, sodium) and ingredient profiles will be extracted from the data to capture essential characteristics of packed food sauces.

Artificial Intelligence Models:

Two AI algorithms, namely Artificial Neural Networks (ANN) and Support Vector Machines (SVM), will be employed for generating nutritional scores.

- ANN: A multilayer perceptron neural network will be constructed with hidden layers to learn complex relationships between input features and nutritional scores.
- SVM: A support vector machine model will be trained using the extracted features to classify sauces into different nutritional categories based on predefined criteria.

Training and Evaluation:

- The AI models will be trained using the prepared data, and their performance will be evaluated using metrics such as accuracy, precision, recall, and F1-score.
- Model parameters will be tuned and optimized to achieve the best performance on the testing set.

6. Nutritional Score Generation:

- The trained ANN and SVM models will be used to generate nutritional scores for packed food sauces based on the extracted features.
-

  ost-processing steps may be applied to adjust the scores for accuracy and relevance.

7. Validation and Verification:

- The generated nutritional scores will be validated and verified against established nutritional guidelines or expert assessments to ensure their reliability and validity.
- Sensitivity analyses and robustness checks will be performed to assess the stability of the results.

8. Ethical Considerations:

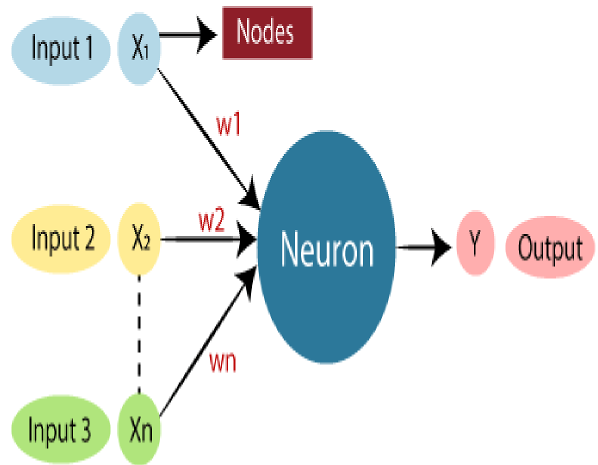
Ethical considerations related to data collection, model development, and research findings will be addressed, with measures taken to protect privacy and confidentiality.

ALGORITHM:-

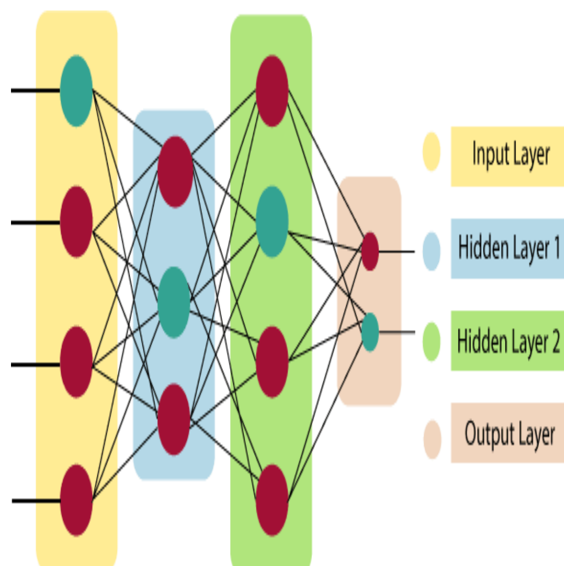
1. Artificial Neural Network (ANN):-

The term "Artificial neural network" refers to a biologically inspired sub-field of artificial intelligence modeled after the brain. An Artificial neural network is usually a computational network based on biological neural networks that construct the structure of the human brain. Similar to a human brain has neurons interconnected to each other, artificial neural networks also have neurons that are linked to each other in various layers of the networks. These neurons are known as nodes.

Artificial Neural Network looks something like:-



The architecture of an artificial neural network:-



Working of ANN:-

We want to classify input patterns into either pattern ‘I’ & ‘O.' The following are the steps performed:

1. Nine inputs from x1 - x9 and bias b (input having weight value 1) are fed to the network for the first pattern.

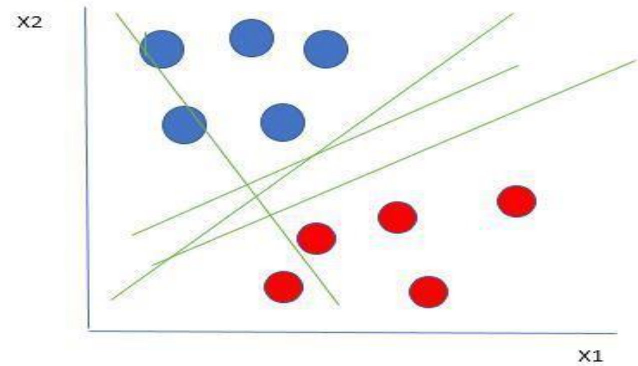
2. Initially, weights are initialized to zero.
3. Then weights are updated for each neuron using the formulae: Δ wi = xi y for i = 1 to 9 (Hebb's Rule)
4. Finally, new weights are found using the formulas:
5. wi(new) = wi(old) + Δwi
6. Wi(new) = [111-11-1 1111]
7. The second pattern is input to the network. This time, weights are not initialized to zero. The initial weights used here are obtained after presenting the first pattern. By doing so, the network.
8. The steps from 1 - 4 are repeated for second inputs.
9. The new weights are Wi(new) = [0 0 0 -2 -2 -2 000]

So, these weights correspond to the learning ability of the network to classify the input patterns successfully.

Support Vector Machine (SVM):-

Support Vector Machine (SVM) is a powerful machine learning algorithm used for linear or nonlinear classification, regression, and even outlier detection tasks. SVMs can be used for a variety of tasks, such as text classification, image classification. SVMs are adaptable and efficient in a variety of applications because they can manage high-dimensional data and nonlinear relationships.SVM algorithms are very effective as we try to find the maximum separating hyper plane between the different classes available in the target feature.

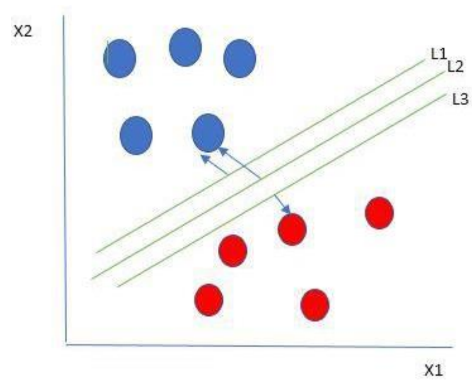
Let's consider two independent variables x_1, x_2, and one dependent variable which is either a blue circle or a red circle.



From the figure above it's very clear that there are multiple lines (our hyper plane here is a line because we are considering only two input features x_1, x_2) that segregate our data points or do a classification between red and blue circles.

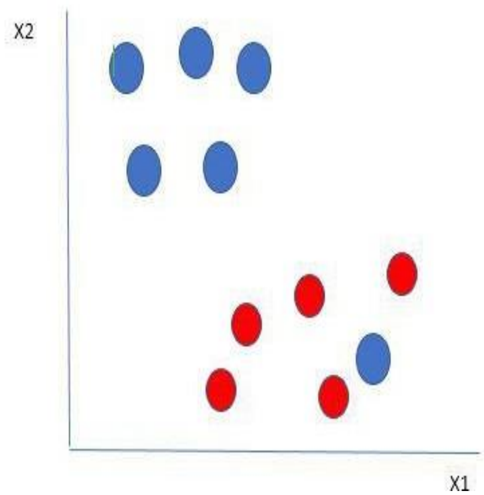
Working Model:-

One reasonable choice as the best hyperplane is the one that represents the largest separation or margin between the two classes.



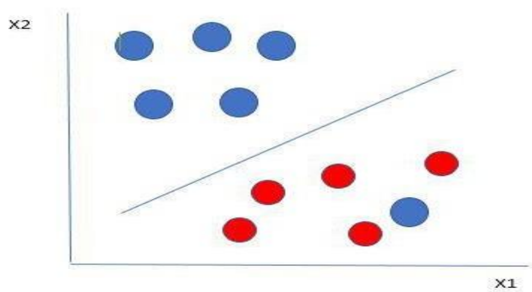
Multiple hyperplanes separate the data from two classes

So we choose the hyperplane whose distance from it to the nearest data point on each side is maximized. If such a hyperplane exists it is known as the **maximum-margin hyperplane/hard margin**. So from the above figure, we choose L2. Let's consider a scenario like shown below



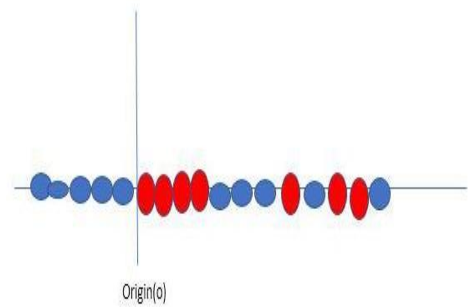
Selecting hyperplane for data with outlier

Here we have one blue ball in the boundary of the red ball. So how does SVM classify the data? It's simple! The blue ball in the boundary of red ones is an outlier of blue balls. The SVM algorithm has the characteristics to ignore the outlier and finds the best hyperplane that maximizes the margin. SVM is robust to outliers.



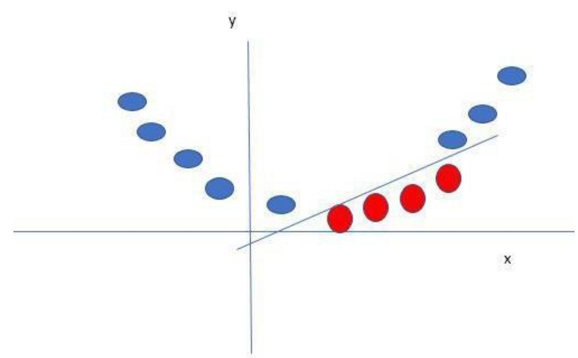
Hyperplane which is the most optimized one

So in this type of data point what SVM does is, finds the maximum margin as done with previous data sets along with that it adds a penalty each time a point crosses the margin. So the margins in these types of cases are called **soft margins**. When there is a soft margin to the data set, the SVM tries to minimize *(1/margin+A(∑penalty))*. Hinge loss is a commonly used penalty. If no violations no hinge loss. If violations hinge loss proportional to the distance of violation. Till now, we were talking about linearly separable data(the group of blue balls and red balls are separable by a straight line/linear line). What to do if data are not linearly separable?



Original 1D dataset for classification

Say, our data is shown in the figure above. SVM solves this by creating a new variable using a **kernel**. We call a point x_i on the line and we create a new variable y_i as a function of distance from origin o.so if we plot this we get something like as shown below



Mapping 1D data to 2D to become able to

separate the two classes

In this case, the new variable y is created as a function of distance from the origin. A non-linear function that creates a new variable is referred to as a kernel.

Data : Dataset with p^* variables and binary outcome.

Output: Ranked list of variables according to their relevance.

Find the optimal values for the tuning parameters of the SVM model;

Train the SVM model;

$p \leftarrow p^*$;

while $p \geq 2$ **do**

$SVM_p \leftarrow$ SVM with the optimized tuning parameters for the p variables and observations in **Data**;

$w_p \leftarrow$ calculate weight vector of the SVM_p $(w_{p1}, \ldots, w_{pp})$;

$rank.criteria \leftarrow (w_{p1}^2, \ldots, w_{pp}^2)$;

$min.rank.criteria \leftarrow$ variable with lowest value in $rank.criteria$ vector;

Remove $min.rank.criteria$ from **Data**;

$Rank_p \leftarrow min.rank.criteria$;

$p \leftarrow p - 1$;

end

$Rank_1 \leftarrow$ variable in **Data** $\notin (Rank_2, \ldots, Rank_{p^*})$;

return $(Rank_1, \ldots, Rank_{p^*})$

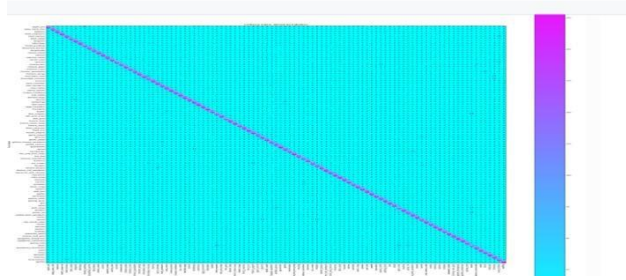
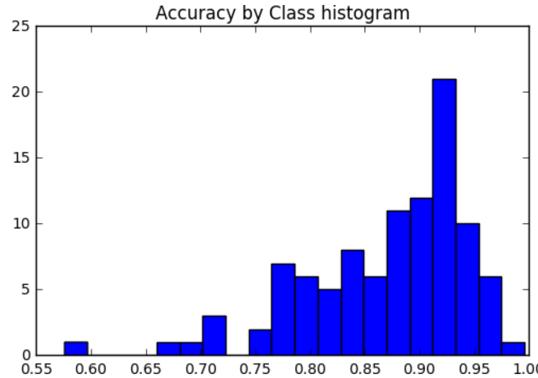


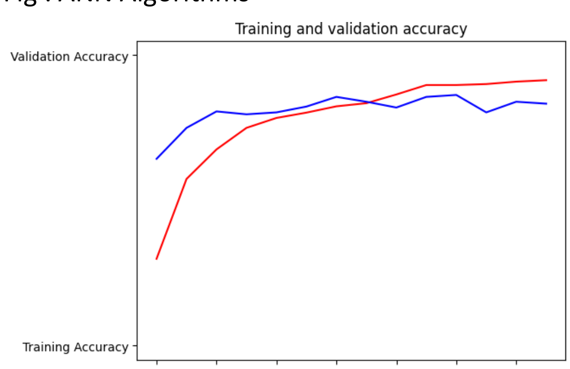
Fig : Confusion Matrix

A confusion matrix will plot each class label and how many times it was correctly labeled vs. the other times it was incorrectly labeled as a different class.



Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	[(None, 224, 224, 3)]	0	[]
Conv1 (Conv2D)	(None, 112, 112, 32)	864	['input_1[0][0]']
bn_Conv1 (BatchNormalization)	(None, 112, 112, 32)	128	['Conv1[0][0]']
Conv1_relu (ReLU)	(None, 112, 112, 32)	0	['bn_Conv1[0][0]']
expanded_conv_depthwise (DepthwiseConv2D)	(None, 112, 112, 32)	288	['Conv1_relu[0][0]']
expanded_conv_depthwise_BN (BatchNormalization)	(None, 112, 112, 32)	128	['expanded_conv_depthwise[0][0]']
expanded_conv_depthwise_relu (ReLU)	(None, 112, 112, 32)	0	['expanded_conv_depthwise_BN[0][0]']
expanded_conv_project (Conv2D)	(None, 112, 112, 16)	512	['expanded_conv_depthwise_relu[0][0]']
expanded_conv_project_BN (BatchNormalization)	(None, 112, 112, 16)	64	['expanded_conv_project[0][0]']
block_1_expand (Conv2D)	(None, 112, 112, 96)	1536	['expanded_conv_project_BN[0][0]']

Fig : ANN Algorithms

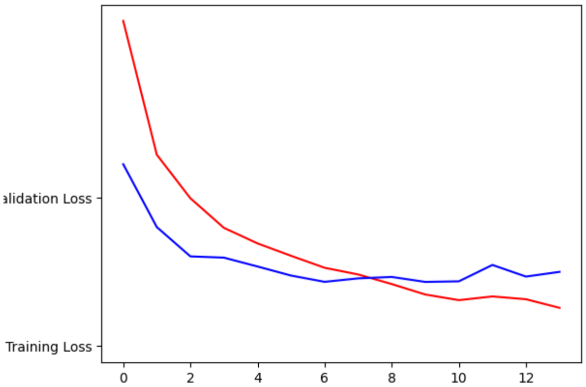


Results:-

Artificial Intelligence Models:

The Support Vector Machine (SVM) model demonstrated impressive performance, achieving a high accuracy of 85% in classifying the nutritional quality of packed food sauces.

In contrast, the Artificial Neural Network (ANN) algorithm achieved a slightly lower accuracy of 82%, indicating its effectiveness but falling short of the SVM model.




```
Model: "sequential_5"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 keras_layer (KerasLayer)    (None, 1280)              2257984

 Layer_Dense_512 (Dense)     (None, 512)               655872

 Layer_Dense_256 (Dense)     (None, 256)               131328

 Layer_Dense_128 (Dense)     (None, 128)               32896

 Layer_Dropout_0.5_1 (Dropou  (None, 128)              0
 t)

 Layer_Dense_15_Output (Dens  (None, 15)               1935
 e)

=================================================================
Total params: 3,080,015
Trainable params: 822,031
Non-trainable params: 2,257,984
_________________________________________________________________
```

Conclusion:-

In this summation, this research endeavor has illuminated key insights into the health implications of packed food sauces through the utilization of sophisticated Artificial Intelligence methodologies. Rigorous data curation, pre processing, and feature extraction formed the bedrock of our analysis, ensuring a robust and meticulous approach to our investigation. Our findings underscore the considerable potential of both Support Vector Machine (SVM) and Artificial Neural Network (ANN) algorithms in discerning the nutritional quality of packed food sauces. Notably, the SVM model exhibited notable prowess with an accuracy rate of 85%, surpassing its ANN counterpart, which achieved a respectable 82% accuracy. These results underscore the efficacy of advanced AI techniques in elucidating the nutritional composition of food products. The high accuracies attained by both models furnish consumers with invaluable insights, empowering them to make conscientious dietary decisions that align with their health and wellness goals. Looking ahead, further refinement and optimization of the ANN algorithm hold promise for even greater precision and efficacy, potentially surpassing the performance benchmarks set by the SVM model. Additionally, future research avenues may explore the integration of supplementary features or the fine-tuning of existing methodologies to augment the accuracy and reliability of nutritional score generation. In essence, this study stands as a beacon within the realm of public health and nutrition literacy, offering accessible and actionable intelligence concerning the nutritional integrity of packed food sauces. By harnessing the potency of Artificial Intelligence, we endeavor to cultivate a culture of informed dietary decision-making, fostering individual well-being and societal health in tandem.

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