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Identification Of Injera Mixture Using Computer Vision And Machine Learning Approach

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Injera is a culturally significant food in Ethiopia, and the majority of the population consumes it daily. It is usually made from teff flour and different variations can include barley, corn, rice, sorghum, wheat, or a combination of these flours. However, the adulteration of Injera with harmful substances poses significant problems. When bad ingredients are mixed with teff flour or other flour, it can lead to health issues for consumers, loss of cultural identity as the traditional preparation and authenticity of Injera, and it creates challenges in marketing and promoting genuine Injera, as consumers may become wary of purchasing products that are not guaranteed to be pure and safe. Addressing these problems is crucial to ensure the preservation of cultural heritage, protect public health, and maintain the integrity of the Injera market. Identification of Injera is difficult using the naked eye due to their similar features. In recent years, machine learning and deep learning algorithms have demonstrated impressive potential in image identification. This paper proposes a hybrid approach based on the best feature extraction algorithm to classify injera mixtures. Using traditional fermentation techniques, we prepared datasets consisting of Injera samples with various combinational ratios including 10:90 and 20:80 ratios. We captured hot Injera before 1 hour and cold Injera after 24 hours. In this study, we have used Grey Level Co-occurrence Matrix (GLCM), Convolutional Neural Network (CNN), and a combination of GLCM and CNN as a feature extraction technique. Also, we have used a Support Vector Machine (SVM) and Random Forest (RF) as a classifier to design the Injera mixture identification system. We have examined different combination ratios of hot and cold (after 24 hours) frontside and backside Injera. From the experimental results, we have registered an accuracy of a combinational ratio of 10:90 frontside hot Injera, 10:90 backside hot Injera, 10:90 frontside cold Injera, 10:90 backside cold Injera, 20:80 frontside hot Injera, 20:80 backside hot Injera, 20:80 frontside cold Injera, 20:80 backside cold Injera is 87%, 86%, 93%, 92%, 91%, 95%, 98%, and 98% for SVM and 88%, 87%, 91%, 91%, 93%, 94%, 98%, and 98% for RF respectively on combined features.

Keywords: CNN; GLCM; Feature Extraction; SVM; Random Forest; Thresholding.

1. Introduction

Ethiopia is a country that has different cultures like eating-based culture, music, and religious cultures. Therefore, Injera is one of the cultural foods of the Ethiopian people. The majority of Ethiopian people consume Injera at least once a day. This cultural food is usually prepared from teff flour, and sometimes it is prepared from

a b c

Fig. 1. Injera image included in this research

barley, corn, rice, sorghum, wheat, and a mixture of those flours. However, Currently, we have heard social media news like a person baked Injera with mixtures of bad things. Additionally, some people cannot eat corn and mixtures of corn Injera in the case of diabetes disease because corn is a high carbohydrate food. In this case, Humans have different challenges in identifying food for their survival.

Injera is not only a staple food but also a symbol of Ethiopian identity and heritage. Its unique taste, texture, and cultural significance have contributed to its popularity both within Ethiopia and in Ethiopian communities around the world.

In this study, injera identification included pure teff injera(a), a mixture of corn with teff(b), and a mixture of "gesso" with teff injera(c) are shown in Fig. 1.

Because of its superior qualities such as strong water-holding capacity, extended shelf life, unique flavor, pliability, and smooth and glossy texture, teff is the most chosen grain for Injera backing over other cereals [1]. Currently, food recognition has attracted more attention in image processing and computer vision. In computer vision, image identification is one of the fundamental tasks and aims to recognize images [8]. To Analyze and understand, the researchers captured food images from different views, such as health, culture, and marketing. Computer vision systems used for automatic external quality control of agricultural products and food industries have worked for decades [14] . The authors in [2], [12] have proposed a method to identify the outside quality of injera using color, texture, size, and shape.

Previous research on identifying food images utilized traditional machine-learning algorithms to extract image features and deep learning for feature extraction and classification. However, end-to-end classification particularly when using deep learning algorithms like CNNs, can come with certain challenges such as high training time, complexity, and computational memory. Additionally, CNN did not extract enough features with a smaller dataset. Traditional machine learning algorithms are also less effective in generalizing and distinguishing important features between highly similar classes.

This paper proposes a hybrid approach based on the best feature extraction algorithm to classify injera mixtures. To collect the Injera image, first, we know the

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combination ratio of teff with 'gesso' and teff with corn before baking Injera. We applied different noise removal and image enhancement techniques based on the noise level of the dataset..

2. Related Works

We have considered some of the other food image recognition systems. This is because there has never been research works on injera. The authors in [10] presents food image classification using SVM. Food images were collected from publicly available resources and online sources. The authors used the FCM algorithm for segmentation and SVM for classification. This paper shows 95% of accuracy. The authors in [4] have proposed a method that combines SIFT and LBP handcrafted features extractions. These extracted features to classified using SVM. The authors collected a dataset in 50 different classes, each class used 100 samples. This paper achieves 68.3% accuracy. As referenced in [11] a food recognition using combined SURF and Gist feature extraction and using SVM to classify the model can be used. This paper uses Gist to provide a holistic description and SURF is scale and rotation invariance. The authors achieve an overall 93.3% accuracy in classification using the SVM model [11]. The authors in [9] have proposed identifying the food item and its calorific value estimation using SVM and an improved multilayer perceptron model (MLP). This paper uses preprocessing, segmentation, and feature extraction techniques for a single food item. The extracted features are fed into SVM and MLP classifiers. Furthermore, [15] present Food/Non-food Image Classification and Food Categorization using a Pre-Trained GoogLeNet Model based on a deep convolutional neural network. Images are collected from existing image databases and social media using imaging devices like smartphones and wearable cameras. This study shows experimental results that indicate a high level of accuracy of 99.2% for food/non-food classification and 83.6 percent for food category recognition.

We have identified the gaps in these related works, which we aim to address in our research. To our knowledge, no previous study has explored the combination of handcrafted features and CNN features for recognizing different classes of food image. In this study, we have introduced a novel approach that utilizes a combination of GLCM (Gray Level Co-occurrence Matrix) and CNN features to distinguish between different classes. By ensemble of features, we aim to enhance the accuracy of injera mixture identification.

3. Methodology

3.1. *Data Collection*

To collect the Injera image, first, we know the combination ratio of teff with Jasso and teff with corn before baking Injera. Therefore, we have mixed the first ratio 20:80 which means 20% gesso with 80% teff and 20% corn with 80% teff. The second

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ratio is 10:90 (10% Jasso with 90% teff and 10% corn with 90% teff). We prepared Injera using traditional fermentation techniques. The process is pure teff, mixtures of gesso with teff, and mixtures of corn with teff flours mixed with water and a seed culture (Ersho) from the previous batch. Then, the mixture was fermented for 2-3 days for primary fermentation. After the initial fermentation, the 'absit' is combined with the primary fermenter and allowed for secondary fermentation for 2 hours. Finally, its fermentation is ready to prepare 'injera'. Therefore, we prepared 'Injera' in the traditional fermentation technique. Images were captured front and backside of hot and cold 'Injera' with Samsung Galaxy S5. We also captured hot Injera before 1 hour and cold 'Injera' after 24 hours.

In our experiment, we used a total of 600 images and 200 images per class of pure teff, Gsso' with teff, and corn with teff 'injera'. We used a total of 4000 images of different ratios of 'teff', mixtures of corn with 'teff', and mixtures of 'gasso' with teff, both hot and cold 'Injera'.

3.2. *Model Design*

The proposed system has a series of steps, preprocessing of images, segmentation, feature extraction, and classification. To identify Injera from a dataset four basic phases are performed. The first phase is preprocessing, in this phase, the interpolation technique is performed initially because resizing images from the one-pixel grid to another is used to minimize the computational time for the next image enhancement steps. The next task in this phase performed image enhancement and color space conversion because it gives an improved visual quality and colors of 'Injera' images. The next phase is segmentation and feature extraction. The extracted features feed into the classifier. Fig. 2. shows the proposed system architecture of our study.

3.2.1. *Preprocessing*

Image preprocessing is a technique used to eliminate unwanted information from images, enhance the visibility of important information, restore valuable data, and simplify the data to improve the accuracy of image feature extraction and identification. The dataset is collected with the different image sizes. Therefore, there are different resize dimensions such as 360x360, 256x256, and 224x224, and achieved better performance during testing the model in 224x224 image size.

Image Enhancement Techniques: the image quality are affected by different factors, like air conditioning and camera nature. To increase the 'injera' image quality, we applied image enhancement techniques. Image enhancement techniques helps to enhance the image and make the processing of the image increase its effectiveness. This method is used to preserve brightness and original information ([13]). Two major types of image enhancement techniques such as: global and local. The global techniques are simple, fast, and suitable for the overall enhancement of the image. However, a different region of the image may not require a different

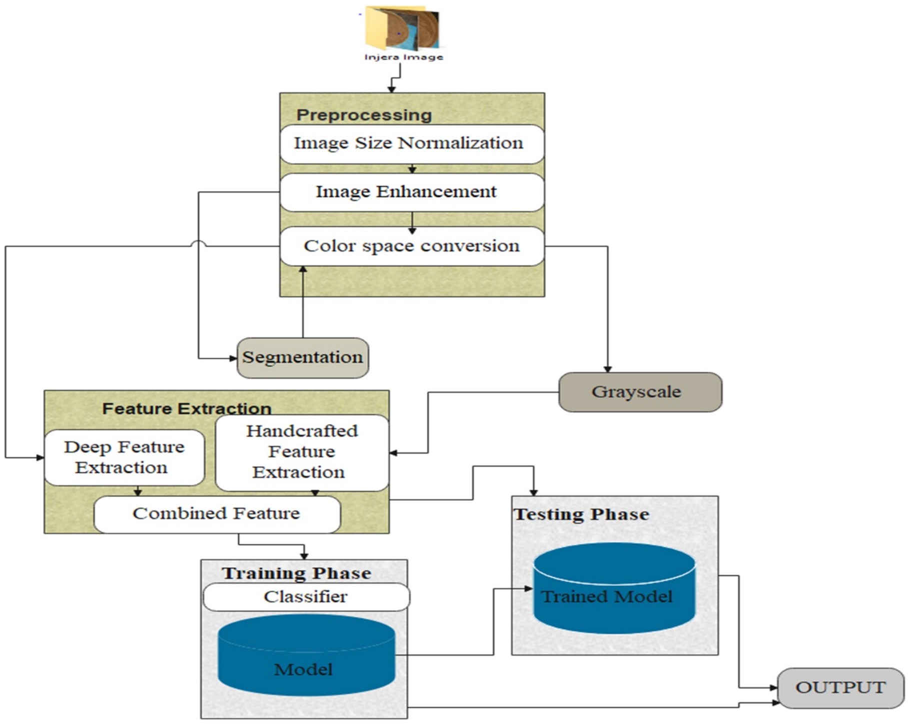

Fig. 2. Proposed system architecture

level of enhancement because only global histogram information over the whole image is applied. In the local enhancement techniques, the neighboring pixel is considered and then adjustments are applied based on the local information. This technique enhances overall contrast more effectively than global techniques ([6]). We used histogram equalization and contrast-limited adaptive histogram equalization (CLAHE).

Histogram Equalization is simple, effective, and low complexity. This technique is used to adjust the image contrast using the image histogram and used to equally distribute various pixel intensities over the entire image allowing lower local contrast areas to gain a higher contrast.

Contrast Limited Adaptive Histogram Equalization (CLAHE): CLAHE is a locally adaptive contrast enhancement technique. CLAHE is an improved version of AHE. Because a limited range of pixels is mapped throughout the whole visualization range, the AHE method has the drawback of over-amplification of noise in homogenous regions of the image. CLAHE is a technique to prevent this over-amplification of noise that occurs when using AHE. CLAHE is used to enhance the brightness level of the image to a specific range and is used to prevent brightness saturation ([6]). This is the reason to use CLAHE in this paper. Fig. 3 shows the dif-

(a) Original image (b) HE image (c) CLAHE image

Fig. 3. Proposed system architecture

ference between the original image, histogram equalization, and Contrast Limited Adaptive Histogram Equalization.

3.2.2. *Feature Extraction*

(A) Features extracted using CNN:

CNN is powerful and achieves better performance in computer vision applications and image recognition. CNN model consists of different layers such as convolution layer, activation layer, pooling layer, fully connected layer, and SoftMax classifier. The model consists of training, validation, and testing phases. During the training phase, different convolutions with activation and pooling operations are stacked on top of each other to learn injera features. After features are extracted, classification is done by a SoftMax classifier. The validation phase is concerned with increasing the accuracy by decreasing the loss, to do this we use the Adaptive Moment Estimation (Adam) optimization algorithm. The number of convolution layers, type of pooling operation, number of filters, and filter size is selected during experimentation.

(B) Features extracted using GLCM:

This method examines the distribution of grey-level pairs of pixels in an injera image. It extracts a variety of features from the GLCM, including contrast, energy, correlation, homogeneity, and entropy. The GLCM is created by calculating the frequency of pairs of grey levels at specific distances and orientations within the image. The most common distance is 1 pixel, and the orientation is typically set to 0, 45, 90, or 135 degrees.

3.2.3. *Classification*

Classification is the final step in image processing, where the given data or input is categorized into the correct class or category based on the extracted features ([7]). Various classification techniques were used to classify the different objects in the image, which is done using machine learning or statistical learning techniques.

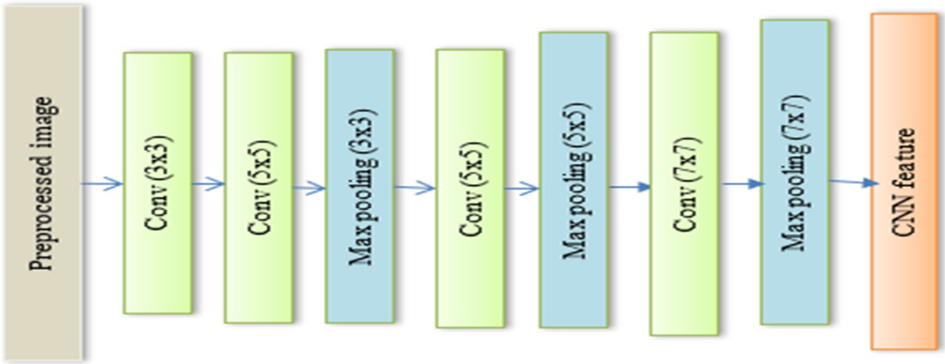

Fig. 4. Feature extraction with CNN

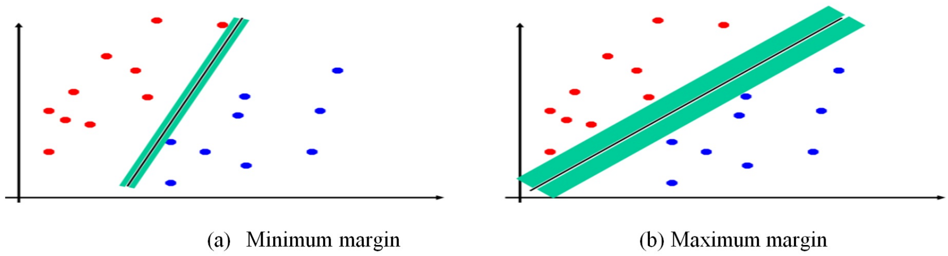

Fig. 5. Margin of SVM

(A) Classification using SVM Classifier:

SVM is a machine learning algorithm. This algorithm is used to classify regression challenges, linear and nonlinear data. The SVM algorithm plots all of the data items in the dataset as points in N-dimensional space (N denotes the number of features). Then we performed classification by finding the hyperplane that separates the class of data points. The main objective of SVM classification is to find the hyperplane that has a maximum margin for each class. The maximum margin means the maximum distance between the hyperplane and each class of data point. If there is a maximum margin, the model will categorize new data to the proper class with more confidence. Fig. 5 shows the difference between maximum margin and minimum margin.

As we can see in Fig. 5, the black line indicates the hyperplane that separates red data points and blue data points. The green shaded region indicates the distance to the hyperplane. When new data points come to a prediction, it is easier in maximum margin than in minimum margin because the distance between the hyperplane and the data points are maximum. The hyperplane is a decision boundary that helps to classify the

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data points. There are different kernel functions, such as Radial Basis Function (RBF), polynomial, linear, and sigmoid are the most common kernel functions ([16]). SVM has hyperparameters like gamma, C (regularization parameter), and degree.

(B) Classification Using Random Forest:

For classification and regression issues, the RF method is used. This method is one of the most popular and efficient algorithms ([5]). RF is a collection of several decision trees it is robust and highly accurate. Because random forest takes the average prediction from the decision trees, it is not vulnerable to overfitting ([3]). The random forest creates decision trees on randomly selected data samples gets predictions for each tree and selects the best solution through voting. RF provides the best indicator of the feature's importance.

4. Results and discussion

4.1. *Dataset*

In this study, Injera images were classified based on its preparation type, such as pure teff 'injera', a mixture of corn with teff, and a mixture of 'gesso' with 'teff' taken from the image stored in our local folder. Noise may occur when capturing images. Therefore, to enhance the image and color quality, the researchers applied sequence of pre-processing techniques, including image enhancement and color enhancement techniques. In our experiment, we used 600 augmented images and 200 images per class of pure teff, 'gasso' with 'teff', and corn with 'teff' injera. We also used 4000 augmented images of different ratios of teff, mixtures of corn with teff, and mixture of 'gasso' with 'teff', both hot and cold Injera.

4.2. *Test results*

In this study, we measured our model's performance using recall, precision, and F1-score. In this section, we clearly showed the difference in the accuracy of the above-stated classifier. We also showed the results of the three features (features extracted by GLCM, features extracted by CNN, and features extracted by a combination of GLCM and CNN). We compared the difference between SVM and RF classifiers based on the results recorded in the experiments.

(A) Experiments on SVM Classifier:

In this study, Image features were extracted using GLCM, CNN, and a hybrid of the two. These extracted features were tested using the SVM classifier. We trained the GLCM feature, CNN feature, and combined feature using the SVM classifier. Grid search is a method of hyper-parameter tuning that builds and evaluates a model methodically for each combination of algorithm parameters specified in the grid. We used grid search to select the optimal parameters from the list of random values of parameters. Table 1 shows the list of random values of parameters.

Table 1. List of random values of SVM parameters

Kernel function	Radial Basis Function (RBF)			Poly
C (regularization parameter)	0.1	1	10	100
Gamma	1	0.1	0.01	1E-3

We used grid search for different ratios of Injera datasets extracted by the GLCM feature, CNN feature, and, combined feature to select the optimal parameters. Therefore, the optimal parameters that are retrieved are listed in the following Table 2.

Table 2. Optimal parameter of SVM

Dataset	Kernel	C	Gamma
10:90 ratio frontside hot Injera extracted by GLCM	RBF	100	0.001
10:90 ratio frontside hot Injera extracted by CNN	RBF	10	0.01
10:90 ratio frontside hot Injera extracted by the combined feature	RBF	10	0.001
10:90 ratio backside hot Injera extracted by GLCM	RBF	100	0.001
10:90 ratio backside hot Injera extracted by CNN	RBF	1	0.001
10:90 ratio backside hot Injera extracted by the combined feature	RBF	10	0.001
10:90 ratio frontside cold (after 24 hours) Injera extracted by GLCM	RBF	100	0.01
10:90 ratio frontside cold Injera extracted by CNN	RBF	1	0.01
10:90 ratio frontside cold Injera extracted by the combined feature	RBF	10	0.001
10:90 ratio backside cold (after 24 hours) Injera extracted by GLCM	RBF	10	0.1
10:90 ratio backside cold Injera extracted by CNN	RBF	10	0.001
10:90 ratio backside cold Injera extracted by the combined feature	RBF	10	0.001
20:80 ratio frontside hot Injera extracted by GLCM	RBF	100	0.001
20:80 ratio frontside hot Injera extracted by CNN	RBF	10	0.001
20:80 ratio frontside hot Injera extracted by the combined feature	RBF	10	0.001
20:80 ratio backside hot Injera extracted by GLCM	RBF	100	0.001
20:80 ratio backside hot Injera extracted by CNN	RBF	1	0.001
20:80 ratio backside hot Injera extracted by the combined feature	RBF	10	0.001
20:80 ratio frontside cold (after 24 hours) Injera extracted by GLCM	RBF	1	1
20:80 ratio frontside cold Injera extracted by CNN	RBF	100	0.01
20:80 ratio frontside cold Injera extracted by the combined feature	RBF	1	0.001
20:80 ratio backside cold (after 24 hours) Injera extracted by GLCM	RBF	1	1
20:80 ratio backside cold Injera extracted by CNN	RBF	1	0.01
20:80 ratio backside cold Injera extracted by the combined feature	RBF	10	0.01

(B) Experiments on RF Classifier:

In this experiment, we trained the GLCM feature, CNN feature, and combined feature on the RF classifier. We used grid search to select the optimal parameters from the list of random values of parameters. Table 3 shows the list of random values of parameters.

Table 3. List of random values of RF parameters

max_depth	80	90	100	110
max_features	2	3		
min_samples_leaf	3	4	5	
min_samples_split	8	10	12	
n_estimators	100	200	300	1000

We used grid search for different ratios of Injera datasets extracted by the GLCM feature, CNN feature, and, combined feature to select the optimal parameters.

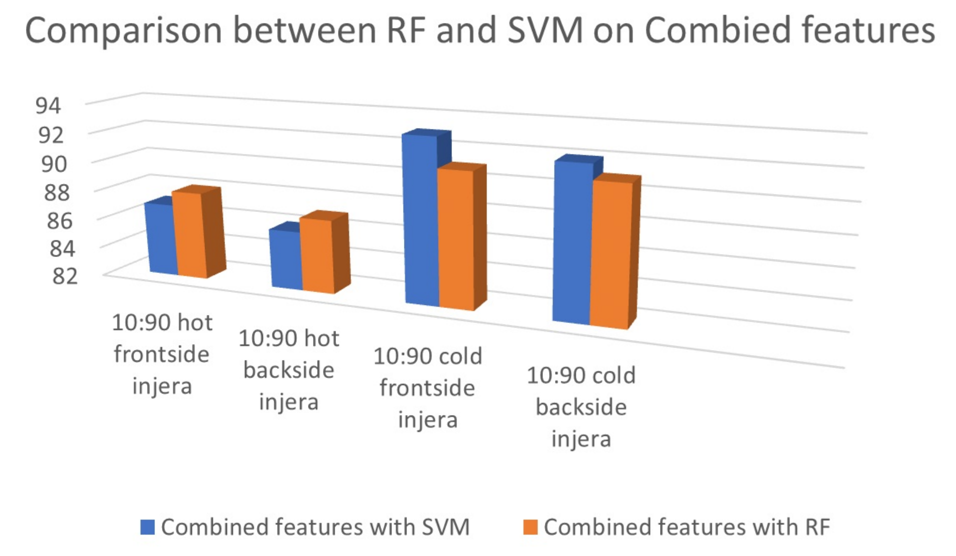
4.2.1. *Comparison of the two classifiers*

The following Fig. 6 illustrates the comparison between SVM and RF classifiers using CLAHE image enhancement and combined features.

As shown in the experiment above recognition rate increased from hot to cold injera (after 24 hours) in both ratios. For SVM and RF classifiers, we used GLCM, CNN, and a combination of CNN and GLCM features. Similarly, CLAHE and HE were used for image enhancement. In comparison, combined CNN and GLCM features and CLAHE images lead a better recognition in both classifiers. As shown in Fig. 6 RF classifier is more suitable than the SVM classifier when an image feature is more similar. As we observed in the above experiments, RF achieves the best results for the hot Injera class in both 10:90 and 20:80 ratios

5. Conclusion

In this study, the design of the Injera identification system focused on three classes: pure teff Injera, mixtures of Jasso with teff, and mixtures of corn with teff, each based on different ratios. To increase useful information on Injera, we examined CLAHE and HE. The examined GLCM, CNN, and combined CNN features in this work was based on the combination features of GLCM and CNN achieved the best results. From the experimental results, we registered an accuracy of a combinational ratio of 10:90 frontside hot Injera, 10:90 backside hot Injera, 10:90 frontside cold Injera, 10:90 backside cold Injera, 20:80 frontside hot Injera, 20:80 backside hot Injera, 20:80 frontside cold Injera, 20:80 backside cold Injera is 87%, 86%, 93%, 92%, 91%, 95%, 98%, and 98% for SVM and 88%, 87%, 91%, 91%, 93%, 94%, 98%, and 98% for RF respectively on combined features.



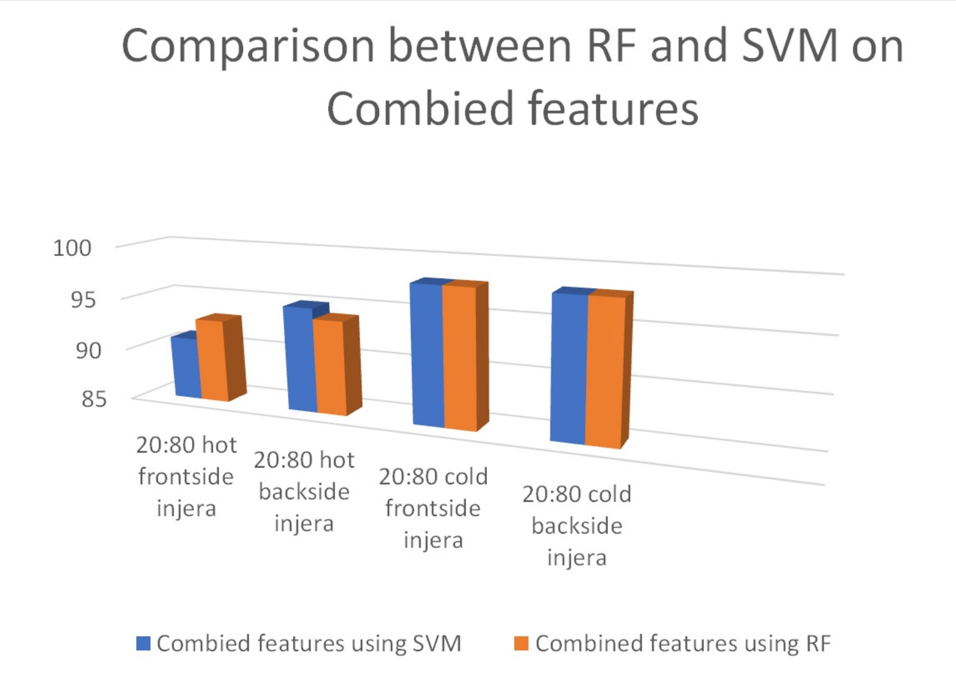


Fig. 6. Comparison of SVM and RF on Combined Features

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