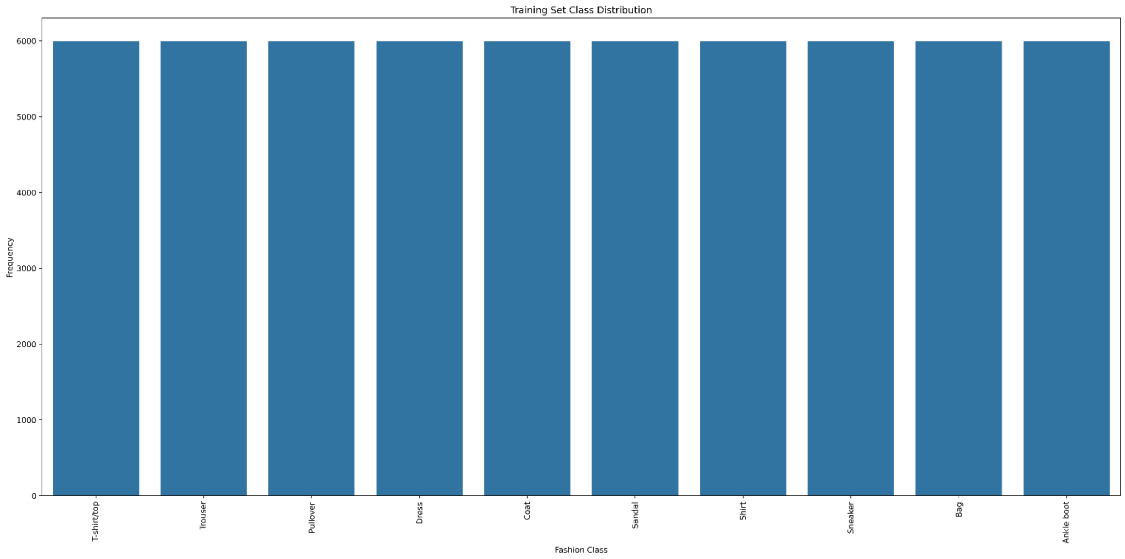
Tema 1 ML

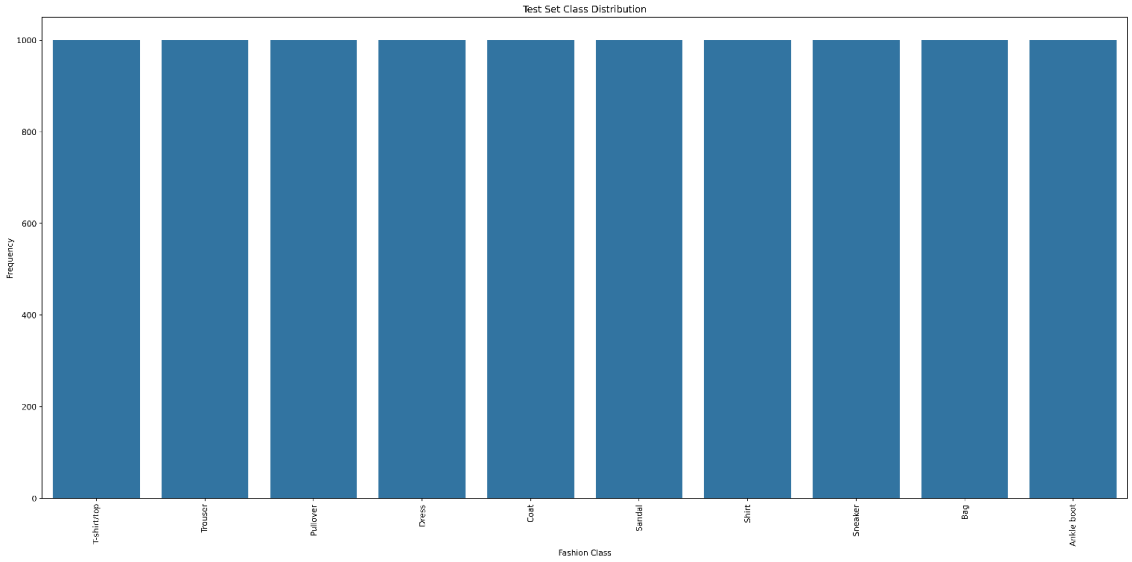
Oana Maria Bacaran, 342C5

Pe datasetul fashion, in etapa de preprocesare, realizam un resize pe toate imaginile din dataset pentru a captura mai multe detalii/features la folosirea metodei HOG. Am folosit metodele de extragere de atribute HOG si PCA in pipeline. Am utilizat HOG deoarece acesta gaseste eficient directiile marginilor, texture si forme si reduce zgomotul pixelilor. In continuare am folosit PCA cu parametrul ncomponents = 50 pentru a pastra cat mai multe features din imaginea initiala si pentru a avea o varianta cat mai mare.

Pe datasetul fashion avem urmatoarele rezultate:

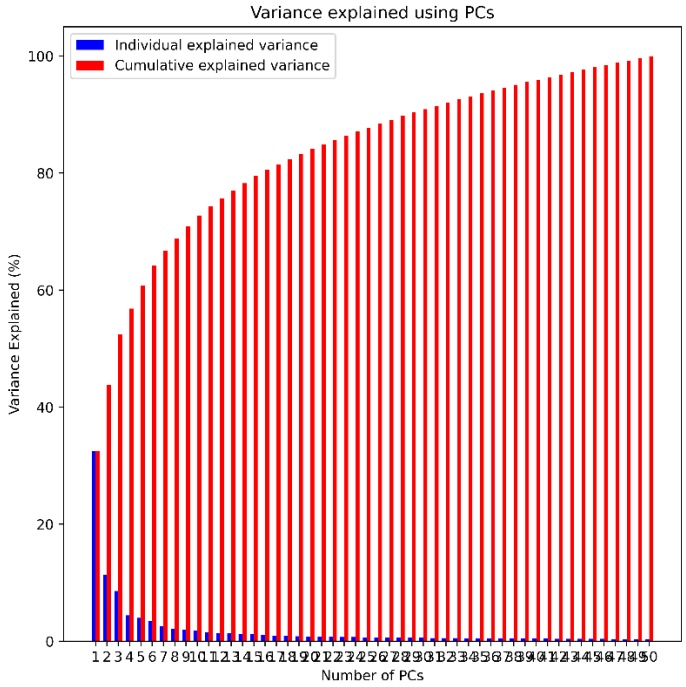
4.2.1. Analiza echilibrului de clase





In imaginile de mai sus a fost realizat analiza echilibrului de clase cu ajutorul unui countplot, folosind biblioteca seaborn. Se observa ca numarul de elemente/imagini, atat in training cat si test, este egal per clasa.

4.2.2 Vizualizare cantitativa



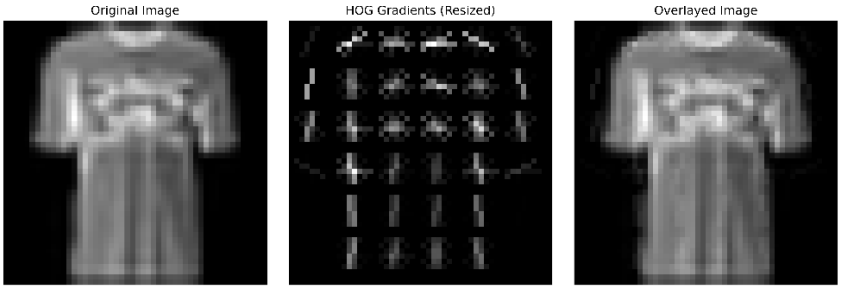
Graficul arată cât de multă informație este explicată de fiecare componentă principală (barele albastre) și cât de multă informație totală este explicată dacă luăm mai multe componente împreună (barele roșii). Observăm că primele componente principale explică cea mai mare parte din varianță, iar după aproximativ 30 de componente, graficul roșu aproape că se stabilizează, ceea ce înseamnă că restul componentelor contribuie foarte puțin.

Acest lucru înseamnă că putem reduce dimensiunea datelor păstrând doar primele 30 de componente, fără să pierdem prea multă informație. Acest lucru ajută la simplificarea procesării datelor și face modelele mai rapide, dar fără să afecteze prea mult performanța. PCA este util aici pentru că elimină redundanțele și ne permite să lucrăm cu mai puține caracteristici.

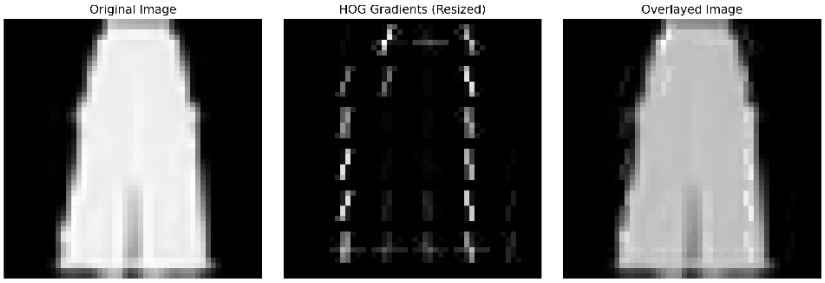
Vizualizare calitativa

Plot-area gradientilor hog peste imaginile initiale (vizualizare intermediara)

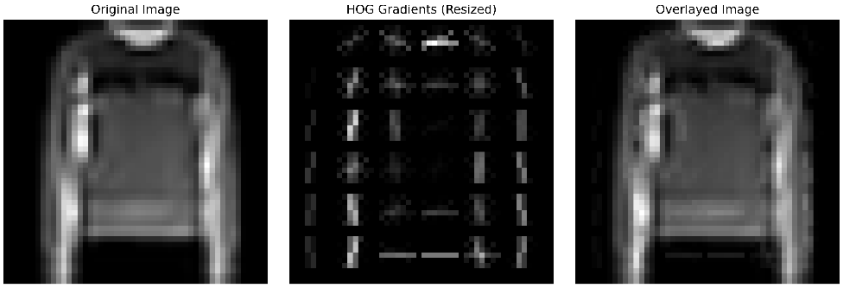
Clasa 0/T-shirt/top



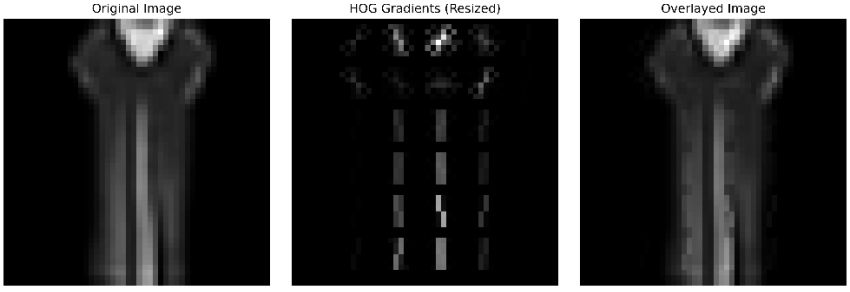
Clasa 1/Trouser



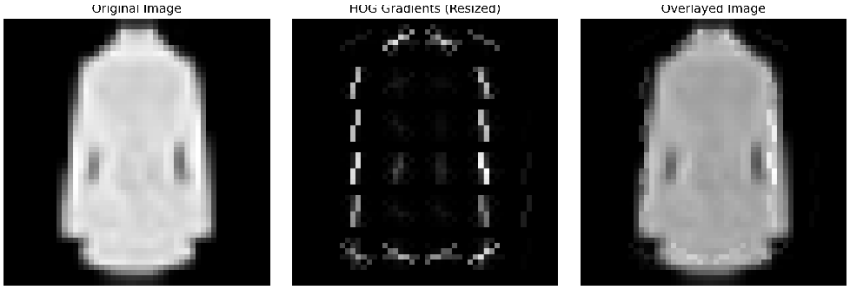
Clasa 2/Pullover



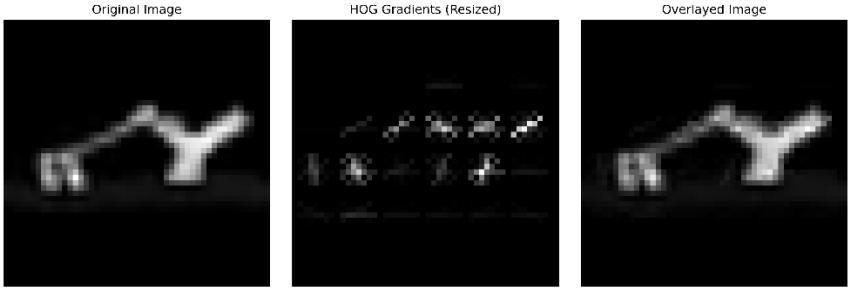
Clasa 3/Dress



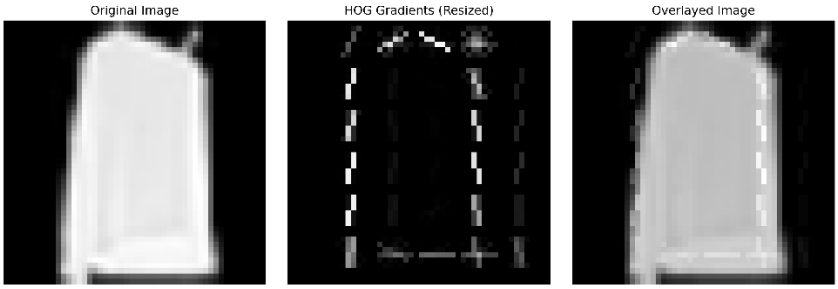
Clasa 4/Coat



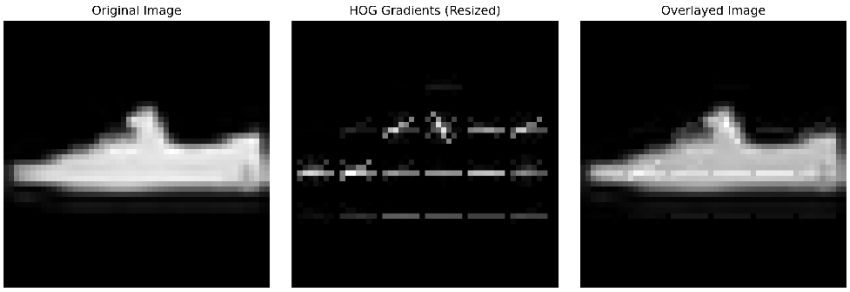
Clasa 5/Sandal



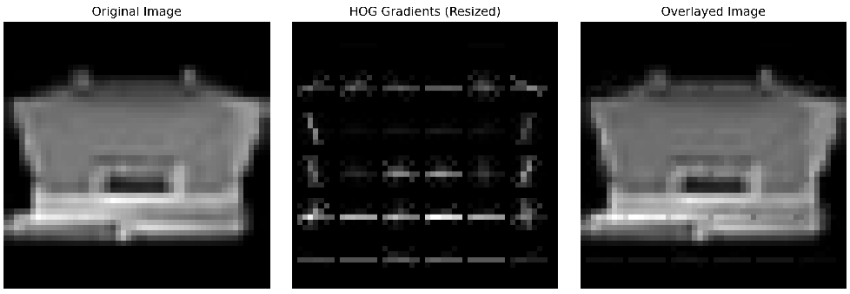
Clasa 6/Shirt



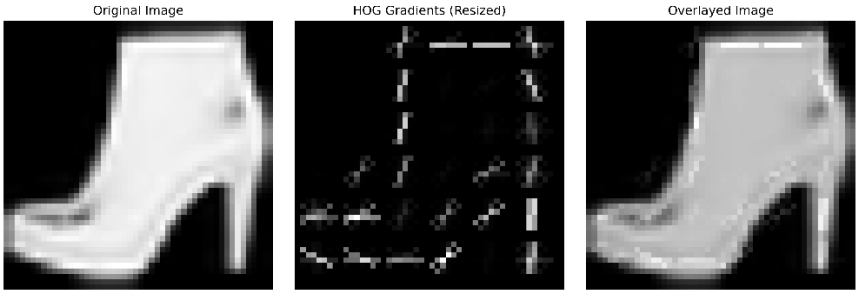
Clasa 7/Sneaker



Clasa 8/Bag



Clasa 9/Ankle boot



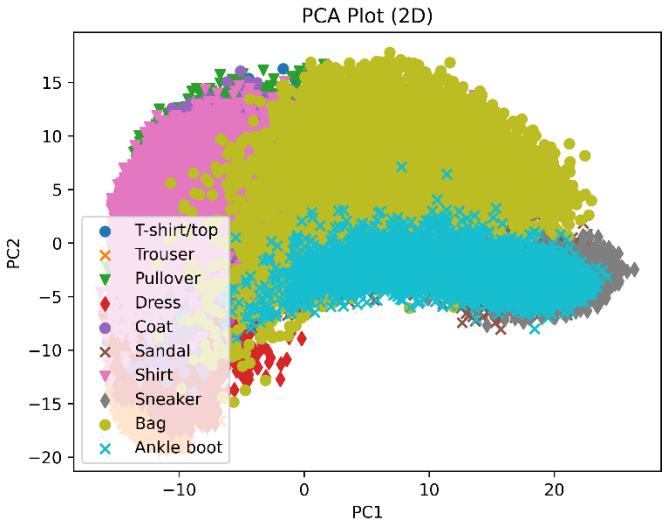
Vizualizare intermediara a aplicarii metodei HOG pe imaginile initiale

Acesta este rezultatul vizualizarii calitative in urma aplicarii HOG pe imagini selectate random din fiecare clasa. Este o modalitate utila de a observa daca cele mai importante margini, contururi si texturi au fost identificate.

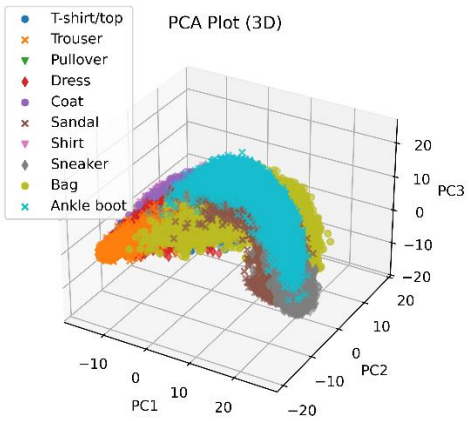
Plot-area componentelor principale

Aceasta metoda de vizualizare calitativa peste hog+pca este utila deoarece putem observa zgomotul si suprapunerea claselor, de asemenea, putem vedea majoritatea informatiei din datele principale intr-un mod mai usor de inteles deoarece avem informatiile comprimate in dimensiuni mai mici.

Pe 2 componente:



Pe 3 componente:



Atat pe vizualizarea bidimensionala cat si pe cea tridimensionala se observa ca clasele sunt bine grupate dar exista suprapuneri semnificative intre ele. Acest lucru sugerează că unele clase pot fi greu de separate doar cu parametrii dati la pca si hog

4.3

Total features before selection: 900

Total features after selection: 675

Setul initial, inaintea aplicarii SelectPercentile, care elimina atributele cu varianta mica, continea toate informatiile calculate in urma aplicarii HOG si a StandardScaler. Dupa aplicararea selectiei, au fost eliminate caracteristicile mai putin relevante, ramanand doar 75% din cele initiale.

4.4

Class 0: T-shirt/top Class 5: Sandal

Class 1: Trouser Class 6: Shirt

Class 2: Pullover Class 7: Sneaker

Class 3: Dress Class 8: Bag

Class 4: Coat Class 9: Ankle boot

	Model	Accuracy	Class 0 Precision	Class 0 Recall	Class 0 F1-Score	Class 1 Precision	Class 1 Recall	Class 1 F1-Score	Class 2 Precision	Class 2 Recall	Class 2 F1-Score	Class 3 Precision	Class 3 Recall	Class 3 F1-Score	Class 4 Precision	Class 4 Recall	Class 4 F1-Score	Class 5 Precision	Class 5 Recall	Class 5 F1-Score	Class 6 Precision	Class 6 Recall	Class 6 F1-Score	Class 7 Precision	Class 7 Recall	Class 7 F1-Score	Class 8 Precision	Class 8 Recall	Class 8 F1-Score	Class 9 Precision	Class 9 Recall	Class 9 F1-Score
0	Logistic Regression	0.737000	0.773000	0.740000	0.756000	0.836000	0.899000	0.866000	0.555000	0.586000	0.570000	0.649000	0.670000	0.659000	0.628000	0.575000	0.600000	0.832000	0.840000	0.836000	0.470000	**0.446000**	0.458000	0.853000	0.832000	0.843000	0.915000	0.868000	0.891000	0.846000	0.914000	0.878000
1	SVM	0.764000	0.730000	**0.776000**	0.752000	0.927000	0.916000	0.922000	0.606000	0.648000	0.626000	0.680000	0.757000	0.716000	**0.662000**	**0.709000**	**0.685000**	0.848000	0.862000	0.855000	**0.569000**	0.442000	**0.497000**	0.857000	0.703000	0.773000	**0.968000**	0.885000	0.925000	0.811000	**0.947000**	0.874000
2	Random Forest	**0.788000**	**0.814000**	0.753000	**0.782000**	**0.960000**	0.922000	**0.941000**	**0.608000**	**0.670000**	**0.637000**	0.696000	**0.864000**	**0.771000**	0.603000	0.654000	0.627000	0.917000	0.907000	0.912000	0.525000	0.340000	0.413000	**0.890000**	**0.875000**	**0.883000**	0.924000	**0.960000**	**0.942000**	**0.912000**	0.938000	**0.925000**
3	XGBoost	0.773000	0.798000	0.764000	0.781000	0.950000	**0.930000**	0.940000	0.561000	0.619000	0.589000	**0.703000**	0.836000	0.764000	0.563000	0.515000	0.538000	**0.927000**	**0.908000**	**0.917000**	0.485000	0.408000	0.443000	0.889000	0.868000	0.879000	0.936000	0.948000	**0.942000**	0.897000	0.938000	0.917000

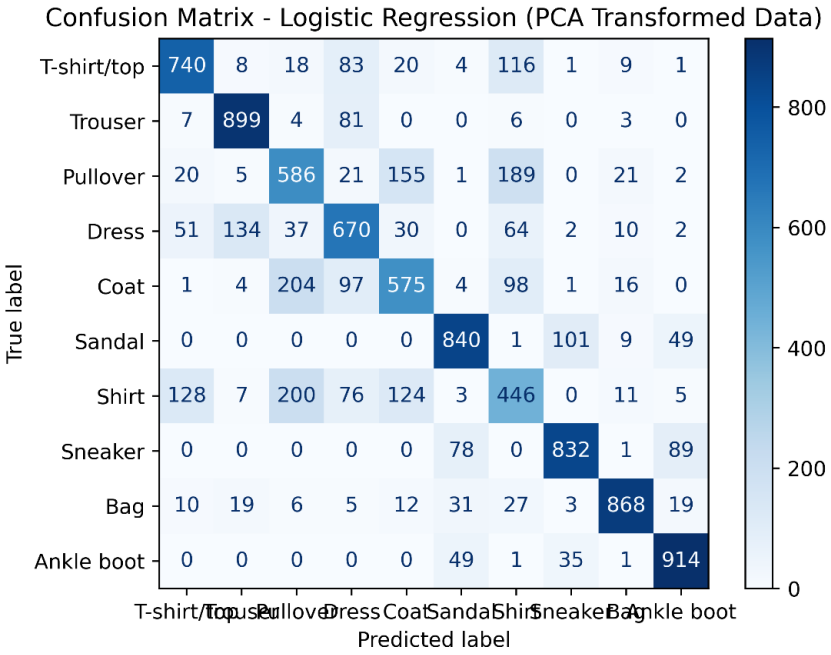
```
Best Logistic Regression Parameters: {'C': np.float64(1.8619556021711627), 'multi_class': 'multinomial'}, Best Score: 0.8601166666666668
Best SVM Parameters: {'C': np.float64(3.6946411021099497), 'kernel': 'poly'}, Best Score: 0.9088999999999999
Best Random Forest Parameters: {'n_estimators': 200, 'max_features': 'log2', 'max_depth': None}, Best Score: 0.87985
Best XGBoost Parameters: {'n_estimators': 300, 'max_depth': 9, 'learning_rate': 0.1}, Best Score: 0.8946666666666667
```

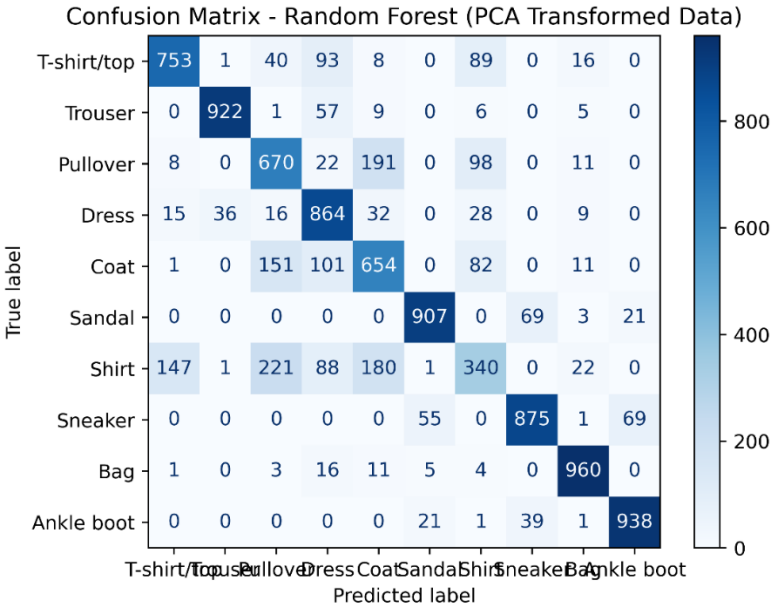
Pentru partea de antrenare, am folosit functia RandomizedSearchCV(cross-validation) pentru a afla cei mai buni parametri, iar apoi am antrenat si prezis pe fiecare model in parte. In urma rularii programului, desi SVM a avut cel mai bun scor, acuratetea generala mai mare a oferit o Random Forest.

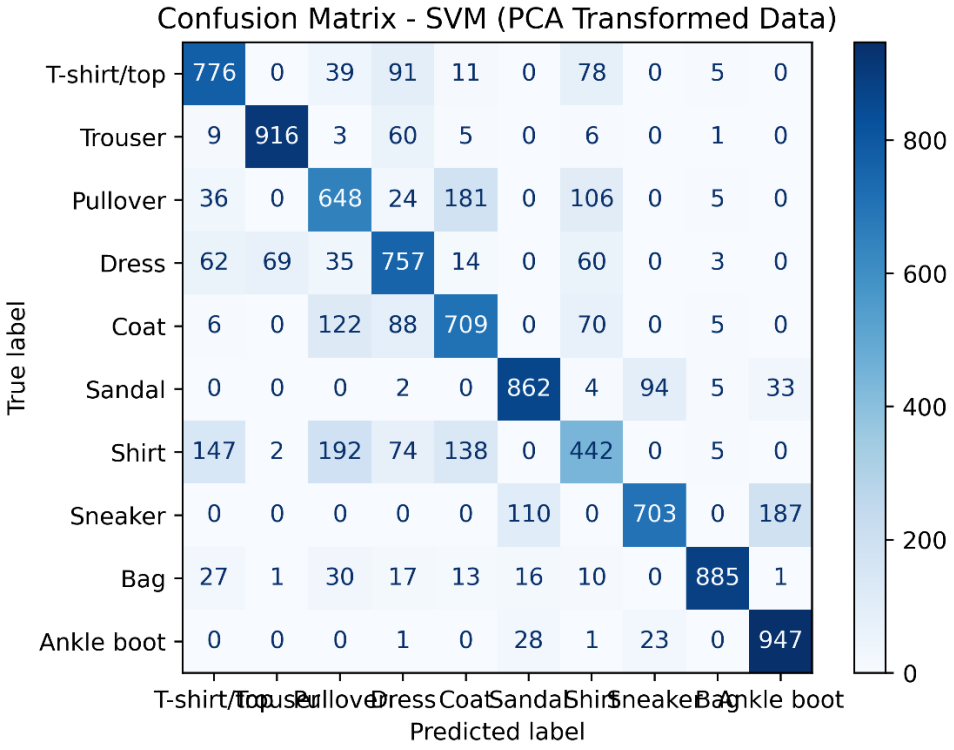
In general, clasele au rezultate bune cu acuratete in jur de 90% (este posibil sa se fi realizat overfit pe unele clase).Clasele cu cele mai bune predictii sunt clasele Trouser, Bag si Ankle boot, deoarece au cea mai mare precizie. Un motiv pentru acest lucru este conturul usor de distins al acestora in urma HOG, si faptul ca au componentele bine grupate in analiza componentelor principale.

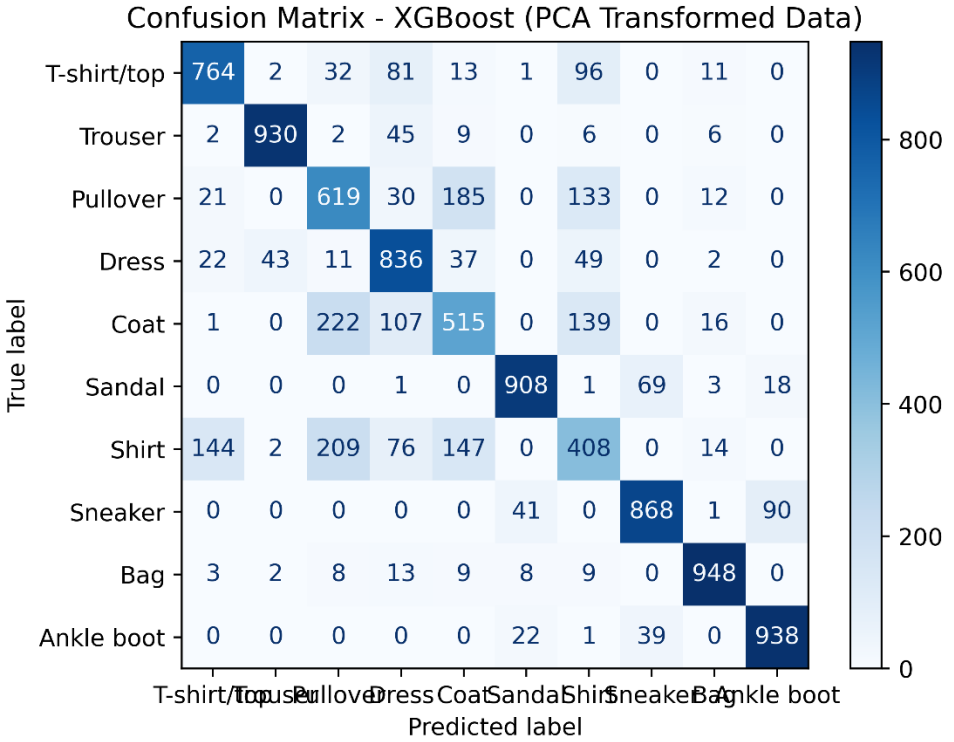
La coada clasamentului se afla clasele Shirt, Coat si Pullover, acestea sunt usor confundabile cand vine vorba de forma lor. Acestea necesita metode mai eficiente pentru o separare eficienta.

Confuzia intre aceste 3 clase poate fi observata si in matricile de confuzie de mai jos, unde exista valori mai mici pe diagonala.


Confusion Matrix - Logistic Regression (PCA Transformed Data)
T-shirt/top 740 8 18 83 20 4 116 1 9 1
Trouser 7 899 4 81 0 0 6 0 3 0
Pullover 20 5 586 21 155 1 189 0 21 2
Dress 51 134 37 670 30 0 64 2 10 2
Coat 1 4 204 97 575 4 98 1 16 0
Sandal 0 0 0 0 0 840 1 101 9 49
Shirt 128 7 200 76 124 3 446 0 11 5
Sneaker 0 0 0 0 0 78 0 832 1 89
Bag 10 19 6 5 12 31 27 3 868 19
Ankle boot 0 0 0 0 0 49 1 35 1 914
True label
T-shirt/top Trouser Pullover Dress Coat Sandal Shirt Sneaker Bag Ankle boot
Predicted label
800
600
400
200
0


Confusion Matrix - Random Forest (PCA Transformed Data)
T-shirt/top 753 1 40 93 8 0 89 0 16 0
Trouser 0 922 1 57 9 0 6 0 5 0
Pullover 8 0 670 22 191 0 98 0 11 0
Dress 15 36 16 864 32 0 28 0 9 0
Coat 1 0 151 101 654 0 82 0 11 0
Sandal 0 0 0 0 0 907 0 69 3 21
Shirt 147 1 221 88 180 1 340 0 22 0
Sneaker 0 0 0 0 0 55 0 875 1 69
Bag 1 0 3 16 11 5 4 0 960 0
Ankle boot 0 0 0 0 0 21 1 39 1 938
True label
T-shirt/top Trouser Pullover Dress Coat Sandal Shirt Sneaker Bag Ankle boot
Predicted label
800
600
400
200
0


Confusion Matrix - SVM (PCA Transformed Data)
T-shirt/top 776 0 39 91 11 0 78 0 5 0
Trouser 9 916 3 60 5 0 6 0 1 0
Pullover 36 0 648 24 181 0 106 0 5 0
Dress 62 69 35 757 14 0 60 0 3 0
Coat 6 0 122 88 709 0 70 0 5 0
Sandal 0 0 0 2 0 862 4 94 5 33
Shirt 147 2 192 74 138 0 442 0 5 0
Sneaker 0 0 0 0 0 110 0 703 0 187
Bag 27 1 30 17 13 16 10 0 885 1
Ankle boot 0 0 0 1 0 28 1 23 0 947
True label
T-shirt/top Trouser Pullover Dress Coat Sandal Shirt Sneaker Bag Ankle boot
Predicted label
800
600
400
200
0

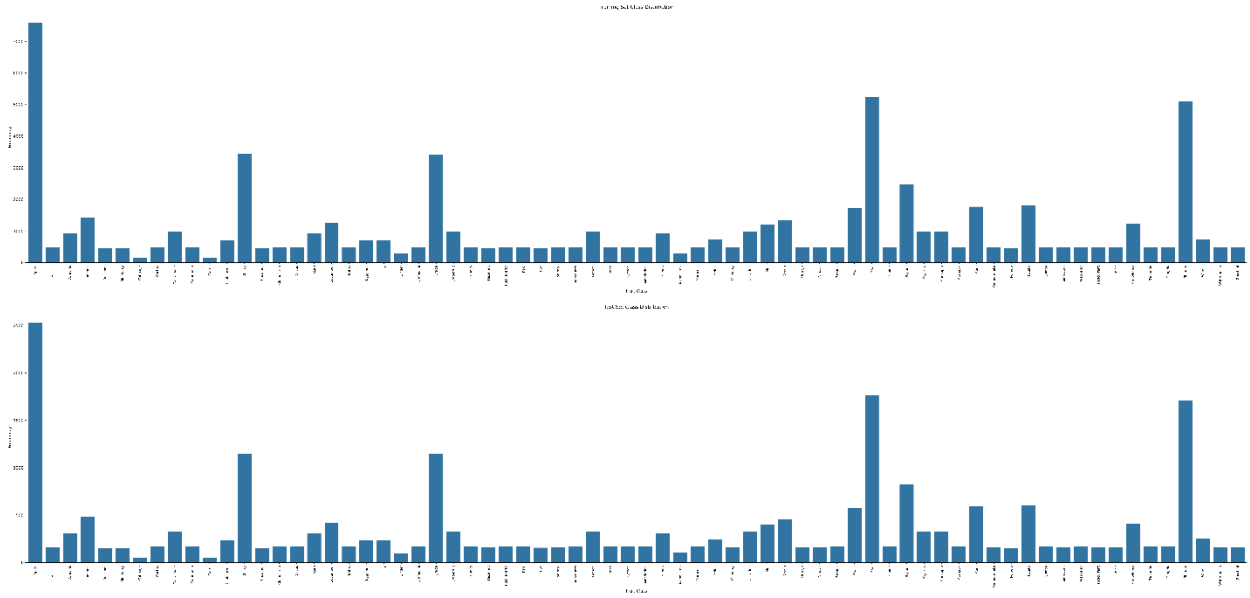

Confusion Matrix - XGBoost (PCA Transformed Data)
T-shirt/top 764 2 32 81 13 1 96 0 11 0
Trouser 2 930 2 45 9 0 6 0 6 0
Pullover 21 0 619 30 185 0 133 0 12 0
Dress 22 43 11 836 37 0 49 0 2 0
Coat 1 0 222 107 515 0 139 0 16 0
Sandal 0 0 0 1 0 908 1 69 3 18
Shirt 144 2 209 76 147 0 408 0 14 0
Sneaker 0 0 0 0 0 41 0 868 1 90
Bag 3 2 8 13 9 8 9 0 948 0
Ankle boot 0 0 0 0 0 22 1 39 0 938
True label
T-shirt/top Trouser Pullover Dress Coat Sandal Shirt Sneaker Bag Ankle boot
Predicted label
800
600
400
200
0

Pe datasetul fruits, am ales să aplic algoritmul ORB datorită vitezei sale ridicate și a acurateței mari în determinarea orientării componentelor imaginii. Acesta este util în captarea detaliilor esențiale caracteristicilor imaginii, fiind un descriptor eficient pentru detectarea și descrierea punctelor de interes. În paralel, am folosit HOG (Histogram of Oriented Gradients) pentru că oferă o descriere robustă a formelor și contururilor din imagini, fiind eficient în analiza texturii și a structurii vizuale a obiectelor, ceea ce este deosebit de util pentru recunoașterea fructelor, care adesea au forme complexe și texturi variate.

Pentru a îmbunătăți performanța clasificării, am combinat features extrase de ambele metode, ORB și HOG, folosind hstack. Astfel, am creat un set de caracteristici mai complet și mai informativ, care poate contribui la o performanță mai bună a modelului, prin captarea atât a detaliilor fine (cu ORB), cât și a informațiilor legate de formele și texturile globale (cu HOG).

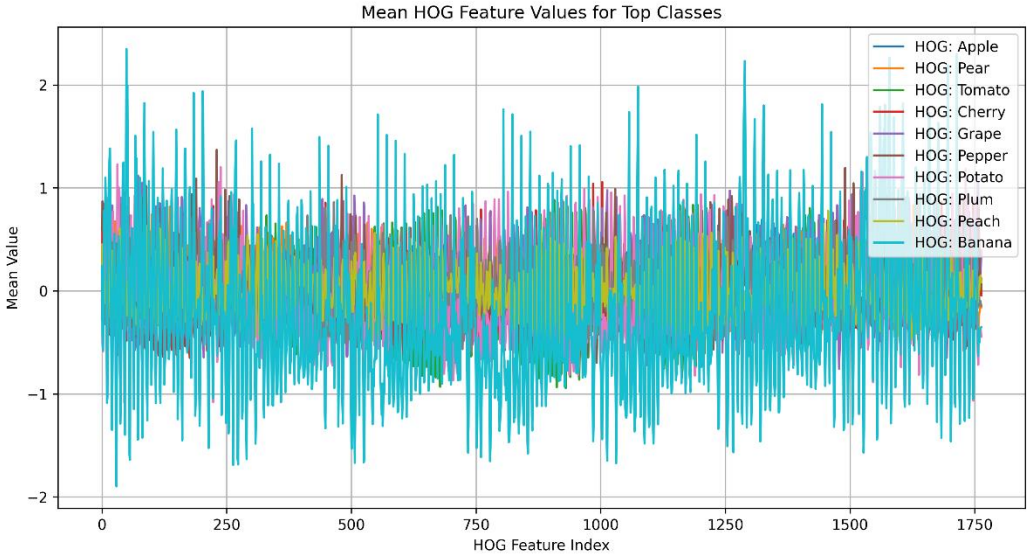
Pe datasetul fruits avem urmatoarele rezultate:

4.2.1. Analiza echilibrului de clase



Am grupat fructele din aceeasi categorie (Apple, Apple 1 si Golden Apple sunt in aceeasi categorie Apple) si au rezultat 70 de clase. Se observa faptul ca exista mai multe imagini la fructele mai commune precum Apple.

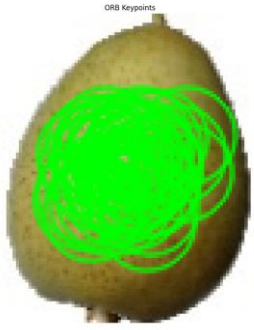
4.2.2 Vizualizare cantitativa



Vizualizarea cantitativa pe HOG de mai sus arata o distributie numerica a valorilor descriptorilor HOG pe top 10 clase, adică a intensității gradientelor într-o gamă de direcții specific.

Vizualizare calitativa

Acesta este rezultatul aplicarii metodei ORB pe fructele ce se afla in top 10. Se observa ca pe unele imagini orb nu a detectat niciun keypoint. O posibililitate a acestuii lucru este faptul ca fie imaginea este prea mica (trebuie redimensionata), fie nu identifica detalii indeajuns de unice.



4.3

Total features before selection: 1796

Total features after selection: 1347

Setul initial, inaintea aplicarii SelectPercentile, care elimina atributele cu varianta mica, continea toate informatiile calculate in urma aplicarii HOG+ORB si a StandardScaler. Dupa aplicararea selectiei, au fost eliminate caracteristicile mai putin relevante, ramanand doar 75% din cele initiale.

Reducerea numărului de caracteristici poate ajuta la prevenirea overfitting-ului a modelului și la îmbunătățirea generalizării, permițându-i să se concentreze pe cele mai relevante trăsături ale datelor.

4.4

La datasetul fruits, nu am mai aplicat cross-validation, ci am realizat un set de validare cu ajutorul functiei train_test_split. Am initializat modelele, apoi am generat combinatii de hiperparametrii predefinti pentru a-l alege pe cei care dau o acuratete mai mare. Modelul era ulterior antrenat cu acesti hiperparametri. Am reusit sa rulez doar Logistic Regression si Random Forest, celelalte doua modele fiind mult prea de durata. Dintre acestea doua, Logistic Regression are acuratetea cea mai mare, la fel si weighted si max average.

Din cele doua matrice de confuzie, se poate observa ca fructul care a fost prezis cel mai bine este Apple, care are si cel mai mare numar de imagini de antrenare. Se poate observa ca in general clasele sunt distinse usor, neexistand valori foarte mari in afara diagonalei principale.

	0	1
Model	**Random Forest_n_estimators=100_max_depth=20_max_features=log2**	Logistic Regression_C=0.1_multi_class=multinomial
Accuracy	0.786000	**0.851000**
Apple Precision	0.497000	**0.802000**
Apple Recall	**0.963000**	0.895000
Apple F1-Score	0.656000	**0.846000**
Apricot Precision	**0.987000**	0.828000
Apricot Recall	0.463000	**0.793000**
Apricot F1-Score	0.631000	**0.810000**
Avocado Precision	0.888000	**0.902000**
Avocado Recall	0.793000	**0.864000**
Avocado F1-Score	0.838000	**0.883000**
Banana Precision	0.946000	**0.973000**
Banana Recall	0.682000	**0.740000**
Banana F1-Score	0.792000	**0.840000**
Beetroot Precision	0.779000	**0.875000**
Beetroot Recall	0.353000	**0.420000**
Beetroot F1-Score	0.486000	**0.568000**
Blueberry Precision	**1.000000**	0.974000
Blueberry Recall	0.675000	**0.734000**
Blueberry F1-Score	0.806000	**0.837000**
Cabbage Precision	**0.979000**	0.887000
Cabbage Recall	**1.000000**	**1.000000**
Cabbage F1-Score	**0.989000**	0.940000
Cactus Precision	**0.879000**	0.844000
Cactus Recall	0.789000	**0.880000**
Cactus F1-Score	0.832000	**0.861000**
Cantaloupe Precision	**0.810000**	0.804000
Cantaloupe Recall	**0.991000**	**0.991000**
Cantaloupe F1-Score	**0.892000**	0.888000
Carambula Precision	**0.989000**	0.975000
Carambula Recall	0.524000	**0.711000**
Carambula F1-Score	0.685000	**0.822000**
Carrot Precision	**1.000000**	**1.000000**
Carrot Recall	**1.000000**	**1.000000**
Carrot F1-Score	**1.000000**	**1.000000**
Cauliflower Precision	0.969000	**1.000000**
Cauliflower Recall	0.940000	**1.000000**
Cauliflower F1-Score	0.954000	**1.000000**
Cherry Precision	0.951000	**0.981000**
Cherry Recall	0.905000	**0.937000**
Cherry F1-Score	0.927000	**0.959000**

Cauliflower F1-Score	0.954000	**1.000000**
Cherry Precision	0.951000	**0.981000**
Cherry Recall	0.905000	**0.937000**
Cherry F1-Score	0.927000	**0.959000**
Chestnut Precision	**1.000000**	0.828000
Chestnut Recall	0.516000	**0.627000**
Chestnut F1-Score	0.681000	**0.714000**
Clementine Precision	**0.991000**	0.948000
Clementine Recall	0.687000	**0.886000**
Clementine F1-Score	0.811000	**0.916000**
Cocos Precision	0.813000	**0.860000**
Cocos Recall	0.813000	**0.928000**
Cocos F1-Score	0.813000	**0.893000**
Corn Precision	**0.730000**	0.641000
Corn Recall	0.480000	**0.487000**
Corn F1-Score	**0.579000**	0.553000
Cucumber Precision	0.865000	**0.902000**
Cucumber Recall	0.767000	**0.859000**
Cucumber F1-Score	0.813000	**0.880000**
Dates Precision	**0.949000**	0.765000
Dates Recall	**0.789000**	0.765000
Dates F1-Score	**0.862000**	0.765000
Eggplant Precision	0.888000	**0.911000**
Eggplant Recall	0.708000	**0.742000**
Eggplant F1-Score	0.788000	**0.818000**
Fig Precision	**1.000000**	0.880000
Fig Recall	0.611000	**0.752000**
Fig F1-Score	0.759000	**0.811000**
Ginger Precision	**0.969000**	0.894000
Ginger Recall	0.636000	**0.768000**
Ginger F1-Score	0.768000	**0.826000**
Granadilla Precision	**1.000000**	**1.000000**
Granadilla Recall	**1.000000**	0.982000
Granadilla F1-Score	**1.000000**	0.991000
Grape Precision	0.790000	**0.890000**
Grape Recall	0.951000	**0.991000**
Grape F1-Score	0.863000	**0.938000**
Grapefruit Precision	**0.994000**	0.991000
Grapefruit Recall	0.952000	**0.961000**
Grapefruit F1-Score	0.972000	**0.975000**
Guava Precision	**1.000000**	0.982000

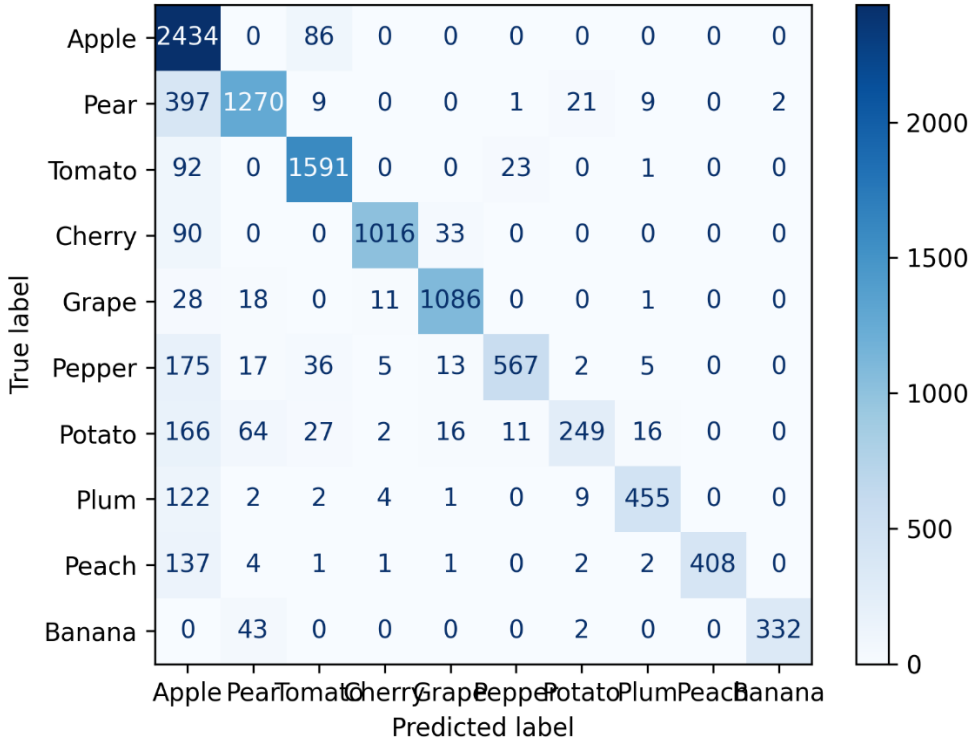
Eggplant Precision	0.888000	**0.911000**
Eggplant Recall	0.708000	**0.742000**
Eggplant F1-Score	0.788000	**0.818000**
Fig Precision	**1.000000**	0.880000
Fig Recall	0.611000	**0.752000**
Fig F1-Score	0.759000	**0.811000**
Ginger Precision	**0.969000**	0.894000
Ginger Recall	0.636000	**0.768000**
Ginger F1-Score	0.768000	**0.826000**
Granadilla Precision	**1.000000**	**1.000000**
Granadilla Recall	**1.000000**	0.982000
Granadilla F1-Score	**1.000000**	0.991000
Grape Precision	0.790000	**0.890000**
Grape Recall	0.951000	**0.991000**
Grape F1-Score	0.863000	**0.938000**
Grapefruit Precision	**0.994000**	0.991000
Grapefruit Recall	0.952000	**0.961000**
Grapefruit F1-Score	0.972000	**0.975000**
Guava Precision	**1.000000**	0.982000
Guava Recall	0.663000	**0.976000**
Guava F1-Score	0.797000	**0.979000**
Hazelnut Precision	**0.994000**	0.952000
Hazelnut Recall	**1.000000**	**1.000000**
Hazelnut F1-Score	**0.997000**	0.975000
Huckleberry Precision	**0.982000**	0.943000
Huckleberry Recall	0.657000	**0.801000**
Huckleberry F1-Score	0.787000	**0.866000**
Kaki Precision	**1.000000**	**1.000000**
Kaki Recall	**0.783000**	0.747000
Kaki F1-Score	**0.878000**	0.855000
Kiwi Precision	0.897000	**0.927000**
Kiwi Recall	0.667000	**0.974000**
Kiwi F1-Score	0.765000	**0.950000**
Kohlrabi Precision	**1.000000**	0.947000
Kohlrabi Recall	**0.580000**	0.573000
Kohlrabi F1-Score	**0.734000**	0.714000
Kumquats Precision	0.940000	**0.947000**
Kumquats Recall	0.952000	**0.976000**
Kumquats F1-Score	0.946000	**0.961000**
Lemon Precision	**0.914000**	0.805000
Lemon Recall	0.933000	**1.000000**
Lemon F1-Score	**0.924000**	0.892000
Limes Precision	**1.000000**	0.944000

Limes Precision	**1.000000**	0.944000
Limes Recall	0.614000	**0.813000**
Limes F1-Score	0.761000	**0.874000**
Lychee Precision	0.941000	**0.960000**
Lychee Recall	0.861000	**1.000000**
Lychee F1-Score	0.899000	**0.979000**
Mandarine Precision	0.981000	**0.985000**
Mandarine Recall	0.633000	**0.783000**
Mandarine F1-Score	0.769000	**0.872000**
Mango Precision	**0.958000**	0.759000
Mango Recall	0.594000	**0.727000**
Mango F1-Score	0.733000	**0.743000**
Mangostan Precision	**1.000000**	**1.000000**
Mangostan Recall	0.627000	**0.912000**
Mangostan F1-Score	0.771000	**0.954000**
Maracuja Precision	0.713000	**0.781000**
Maracuja Recall	0.614000	**0.711000**
Maracuja F1-Score	0.660000	**0.744000**
Melon Precision	**0.882000**	0.838000
Melon Recall	0.854000	**0.992000**
Melon F1-Score	0.868000	**0.909000**
Mulberry Precision	0.924000	**0.970000**
Mulberry Recall	0.970000	**0.994000**
Mulberry F1-Score	0.946000	**0.982000**
Nectarine Precision	**0.951000**	0.465000
Nectarine Recall	0.299000	**0.364000**
Nectarine F1-Score	**0.455000**	0.408000
Nut Precision	**0.995000**	0.821000
Nut Recall	0.505000	**0.720000**
Nut F1-Score	0.670000	**0.767000**
Onion Precision	**0.709000**	0.603000
Onion Recall	0.643000	**0.783000**
Onion F1-Score	0.674000	**0.681000**
Orange Precision	**1.000000**	0.894000
Orange Recall	**1.000000**	**1.000000**
Orange F1-Score	**1.000000**	0.944000
Papaya Precision	0.736000	**0.792000**
Papaya Recall	0.561000	**0.695000**
Papaya F1-Score	0.637000	**0.740000**
Passion Precision	0.961000	**0.986000**
Passion Recall	0.596000	**0.861000**
Passion F1-Score	0.736000	**0.920000**

Papaya Recall	0.561000	**0.695000**
Papaya F1-Score	0.637000	**0.740000**
Passion Precision	0.961000	**0.986000**
Passion Recall	0.596000	**0.861000**
Passion F1-Score	0.736000	**0.920000**
Peach Precision	**0.964000**	0.818000
Peach Recall	0.693000	**0.735000**
Peach F1-Score	**0.806000**	0.774000
Pear Precision	0.648000	**0.693000**
Pear Recall	0.714000	**0.837000**
Pear F1-Score	0.680000	**0.758000**
Pepino Precision	**0.953000**	0.904000
Pepino Recall	0.614000	**0.620000**
Pepino F1-Score	**0.747000**	0.736000
Pepper Precision	**0.925000**	0.823000
Pepper Recall	0.714000	**0.783000**
Pepper F1-Score	**0.806000**	0.803000
Physalis Precision	**1.000000**	0.962000
Physalis Recall	0.930000	**0.991000**
Physalis F1-Score	0.964000	**0.976000**
Pineapple Precision	0.875000	**0.945000**
Pineapple Recall	**0.982000**	0.942000
Pineapple F1-Score	0.926000	**0.944000**
Pitahaya Precision	**1.000000**	0.988000
Pitahaya Recall	0.693000	**0.982000**
Pitahaya F1-Score	0.819000	**0.985000**
Plum Precision	**0.828000**	0.747000
Plum Recall	0.727000	**0.846000**
Plum F1-Score	0.774000	**0.793000**
Pomegranate Precision	**0.969000**	0.958000
Pomegranate Recall	0.384000	**0.689000**
Pomegranate F1-Score	0.550000	**0.801000**
Pomelo Precision	**0.983000**	0.929000
Pomelo Recall	0.739000	**0.941000**
Pomelo F1-Score	0.843000	**0.935000**
Potato Precision	0.449000	**0.744000**
Potato Recall	0.428000	**0.581000**
Potato F1-Score	0.438000	**0.652000**
Quince Precision	**1.000000**	**1.000000**
Quince Recall	0.681000	**0.729000**
Quince F1-Score	0.810000	**0.843000**
Rambutan Precision	0.994000	**1.000000**

Potato F1-Score	0.438000	**0.652000**
Quince Precision	**1.000000**	**1.000000**
Quince Recall	0.681000	**0.729000**
Quince F1-Score	0.810000	**0.843000**
Rambutan Precision	0.994000	**1.000000**
Rambutan Recall	0.970000	**0.982000**
Rambutan F1-Score	0.981000	**0.991000**
Raspberry Precision	0.835000	**0.947000**
Raspberry Recall	0.699000	**0.747000**
Raspberry F1-Score	0.761000	**0.835000**
Redcurrant Precision	**1.000000**	**1.000000**
Redcurrant Recall	**1.000000**	**1.000000**
Redcurrant F1-Score	**1.000000**	**1.000000**
Salak Precision	**1.000000**	0.920000
Salak Recall	0.994000	**1.000000**
Salak F1-Score	**0.997000**	0.959000
Strawberry Precision	0.852000	**0.876000**
Strawberry Recall	0.761000	**0.934000**
Strawberry F1-Score	0.804000	**0.904000**
Tamarillo Precision	0.982000	**0.988000**
Tamarillo Recall	0.970000	**1.000000**
Tamarillo F1-Score	0.976000	**0.994000**
Tangelo Precision	**1.000000**	0.878000
Tangelo Recall	0.717000	**1.000000**
Tangelo F1-Score	0.835000	**0.935000**
Tomato Precision	0.876000	**0.905000**
Tomato Recall	**0.941000**	0.920000
Tomato F1-Score	0.908000	**0.913000**
Walnut Precision	0.827000	**0.915000**
Walnut Recall	**1.000000**	**1.000000**
Walnut F1-Score	0.905000	**0.956000**
Watermelon Precision	**1.000000**	0.903000
Watermelon Recall	**0.675000**	0.650000
Watermelon F1-Score	**0.806000**	0.756000
Zucchini Precision	0.847000	**0.856000**
Zucchini Recall	**1.000000**	**1.000000**
Zucchini F1-Score	0.917000	**0.922000**
Macro Avg Precision	**0.914000**	0.891000
Macro Avg Recall	0.752000	**0.843000**
Macro Avg F1-Score	0.809000	**0.860000**
Weighted Avg Precision	0.835000	**0.856000**
Weighted Avg Recall	0.786000	**0.851000**
Weighted Avg F1-Score	0.788000	**0.849000**

n_estimators=100_max_depth=20_max_features=log2 Confusion Matrix (HC



ic Regression_C=0.1_multi_class=multinomial Confusion Matrix (HOG+ORB)