Bank Note Authentication

C. SREE POOJITHA VARMA
JYOTHI TELI

About

- Banknote authentication refers to the process of verifying the authenticity of paper currency to ensure it is genuine and not counterfeit.
- ▶ With the advancement of technology, counterfeiters have become increasingly sophisticated.
- ▶ Here are some common techniques used for banknote authentication:
- Security Features
- Ultraviolet (UV) Light
- Magnetic Ink Detection
- Microscopic Inspection

PROBLEM

- Our task is to predict whether a bank currency note is authentic or not based upon attributes of the note.
- This is a binary classification problem and we will use knn algorithm to solve this problem. the rest of the section consists of standard machine learning steps.
- Data were extracted from images that were taken from genuine and forged banknote-like specimens for digitization.
- What tool to use to extract the attributes from the notes?
- Which Machine Learning model need to be used to predict the legitimacy of the note?

Introduction

- Trust: Checking banknotes ensures trust in transactions by preventing fake money from circulating.
- Stability: Authentication maintains economic stability by stopping counterfeit money from damaging the economy.
- Global Issue: Counterfeit currency affects everyone, so we need reliable systems to prevent its spread.
- Security Features: Banknotes have special marks like watermarks that show they're real.
- ▶ Prevention: Authentication systems are crucial for stopping fake money and keeping transactions secure.

Software Requirements Specifications (SRS)

- Python
- Logistic Regression
- ► K_Nearest-Neighbour
- Support Vector Machine
- Dataset

Dataset

- ▶ BankNote dataset- https://www.kaggle.com/datasets/shanks0465/banknoteauthentication
- ▶ The dataset is based upon four attributes of the note:
- Skewness
- Variance
- Entropy
- Curtosis

DATASET OVERVIEW

4	Α	В	C	D	Е	F	G	Н
1	Variance	Skewness	Curtosis	Entropy	Class			
2	3.6216	8.6661	-2.8073	-0.44699	0			
3	4.5459	8.1674	-2.4586	-1.4621	0			
4	3.866	-2.6383	1.9242	0.10645	0			
5	3.4566	9.5228	-4.0112	-3.5944	0			
6	0.32924	-4.4552	4.5718	-0.9888	0			
7	4.3684	9.6718	-3.9606	-3.1625	0			
8	3.5912	3.0129	0.72888	0.56421	0			
9	2.0922	-6.81	8.4636	-0.60216	0			
10	3.2032	5.7588	-0.75345	-0.61251	0			
11	1.5356	9.1772	-2.2718	-0.73535	0			
12	1.2247	8.7779	-2.2135	-0.80647	0			
13	3.9899	-2.7066	2.3946	0.86291	0			
14	1.8993	7.6625	0.15394	-3.1108	0			
15	-1.5768	10.843	2.5462	-2.9362	0			
16	3.404	8.7261	-2.9915	-0.57242	0			
17	4.6765	-3.3895	3.4896	1.4771	0			
18	2.6719	3.0646	0.37158	0.58619	0			
19	0.80355	2.8473	4.3439	0.6017	0			
20	1.4479	-4.8794	8.3428	-2.1086	0			
21	5.2423	11.0272	-4.353	-4.1013	0			
22	5.7867	7.8902	-2.6196	-0.48708	0			

MACHINE LEARNING MODEL

Logistic Regression

Predictive statistical model for binary classification problems.

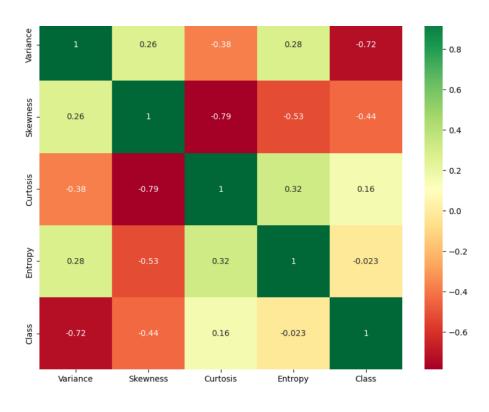
K Nearest Neighbour

Non-parametric method for pattern recognition, classification, and regression.

Support Vector Machine

Effective for classification and regression tasks in machine learning.

HEATMAP ANALYSIS



ALGORITHIM COMPARISON

Logistic Regression

- log = LogisticRegression()
 log_model = log.fit(X_train, y_train)
 log_model.score(X_test, y_test)
- → 0.9801324503311258

KNN

```
[ ] knn = KNeighborsClassifier()
   knn_model = knn.fit(X_train, y_train)
   knn_model.score(X_test, y_test)
```

1.0

Support Vector Machine

```
[[151 2]
   [ 2 120]]
                          recall f1-score support
               precision
                   0.99
                            0.99
                                      0.99
                                                153
                   0.98
                            0.98
                                      0.98
                                                122
                                      0.99
                                                275
     macro avg
                   0.99
                            0.99
                                      0.99
                                                275
  weighted avg
                   0.99
                            0.99
                                      0.99
                                                275
```

0.9854545454545455

TESTING



	variance	skewness	curtosis	entropy
0	0.424469	0.765542	-0.383330	-0.587638
1	-0.223275	1.076167	-1.062076	-0.644263
2	-0.107552	0.884557	-0.813739	-0.944083
3	-0.741536	1.710000	0.370490	-1.784561
4	0.725912	1.277560	-1.088273	-0.127902



\Rightarrow		Variance	Skewness	Curtosis	Entropy	Class	
	762	-1.39710	3.31910	-1.392700	-1.99480	1	11.
	763	0.39012	-0.14279	-0.031994	0.35084	1	
	764	-1.66770	-7.15350	7.892900	0.96765	1	

PREDICTING THE LEGITIMACY

```
[ ] knn_model.predict([[3.62160, 8.6661, -2.8073, -0.44699]])
    array([0])

[ ] knn_model.predict([[-2.54190 ,-0.65804, 2.684200, 1.19520]])
    array([1])
```

CONCLUSION

- Bank authentication, powered by machine learning and data analysis.
- ▶ It plays a vital role in upholding financial integrity by preventing counterfeit currency from circulating.
- With continuous advancements in technology and vigilant implementation of authentication measures.
- ▶ We can maintain trust in the monetary system and secure economic stability for all.

FUTURE ENHANCEMENTS

- Advanced Technologies Integration
- Improved Data Analysis
- Real-time Verification
- Multi-modal Authentication
- User-Friendly Interfaces

REFERENCES

- https://www.kaggle.com/datasets/shanks0465/banknoteauthentication
- https://www.researchgate.net/publication/323223299_Analysis_of_Banknote_Authentication_System_using_Machine_Learning_Techniques
- https://ieeexplore.ieee.org/document/7164721
- https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8590640/
- https://eprints.utem.edu.my/id/eprint/14103/1/paperSyuhadaSciIntLahore.pdf

Team Work

Poojitha's Work

- Algorithms exploring
- Implications of algorithms
- Testing
- Suitable model Prediction

Jyothi's Work

- Data Set Exploration
- ► Literature survey
- ▶ Cleaning Data set
- ► Algorithms Comparison

Thank YOU