SVM-Based Models for Pill Shape Classification

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Abstract

This paper presents a competitive solution for pill shape classification using support vector machines (SVM) models with interpretable features. Our first experiment shows the our SVM model outperforms concolutional neural network (CNN) approaches for pill shape classification. Our second experiment provides a human-in-the-loop approach that was able to achieve an overall classification rate of about 97.83% and a mean precision of 98.4%. The human-in-the-loop component only decided which variables to use for a given pair of meta-classes, or groups of classes. Our multinomial classification problem was converted into a series of binary classification problem through the use of meta-classes. Furthermore, by using variables which have a clear meaning, we created a model which is far more interpretable than its CNN counterparts. The code is available at https://github.com/billyl320/human_decision_tree_pills and https://github.com/billyl320/SPEI-Paper/tree/nml_nih.

Keywords: Shape Classification, Medical Pills, Machine Learning Applications

1 Introduction

A system to identify medical pills would be helpful to the health community. The National Institute of Health's National Library of Medicine (NLM) hosted a competition to encourage research in this area (NML, 2016). However, pill identification models are not currently accurate enough (Maddala et al., 2017). Thus, an approach which classifies pill shapes and is explainable would be useful.

1.1 Related Work

Convolutional neural networks (CNNs) are a popular modeling technique for classifying images in the computer vision community (Gu et al., 2018). One of the benefits of using a CNN is that they are highly predictive. Unfortunately, this high performance is at the cost of the interpretability of the model (Krizhevsky et al., 2012).

Maddala *et al.* presented the most recent human-in-the-loop (HILT) models for pill shape classification (Maddala et al., 2017). However, none of these models provide a straightforward physical interpretation.

1.2 Contributions

In this paper, we provide support vector machines (SVM) models using at most eight variables to classify pill shapes. These approaches provide more competitive classifications when compared to other modeling approaches such as CNNs. Furthermore, these approaches are more interpretable as the features used in the models all have intuitive meanings. The data and code to perform this experiment are provided in the associated GitHub links[1,2].

2 Methods and Materials

In this section, we will discuss the technical details of our data, metrics used, and our models. Since our approach uses interpretable metrics, our models are more understandable than any current CNN-based approach.

2.1 Data

We used the publically available NLM dataset (NML, 2016). The provided reference data had a total of 2000 medical pills on a uniform gray background. We first extracted the pills' shapes and then collected our variables. Table 1 provides the class counts.

Table 1: Table shows the classes and counts of the classes of the NLM NIH reference data.

Class	Capsule	Diamond	Hexagon	Oval
Counts	332	12	8	688
Class	Pentagon	Rectangle	Round	Semi-Circle
Counts	12	6	904	4
Class	Square	Tear	Trapezoid	Triangle
Counts	8	10	4	12

2.2 Metric Collection

The first metrics were the shape proportions, SP, and encircled image-histograms, which is collected from the

[1] https://github.com/billyl320/human_decision_tree_pills
[2] https://github.com/billyl320/SPEI-Paper/tree/nml_nih

shape proportion and encircled image-histogram (SPEI) algorithm (Lamberti et al., NA). The other shape metrics collected that were used in the model were the eigenvalues of the shapes, eccentricity (Kinser, 2018), and circularity (Kinser, 2018). These metrics were of particular interest to us since many were used in other problems that outperformed CNN-based solutions (Lamberti, 2020).

2.3 Model

For the completely machine driven model, we used a subset of the classes. We built a CNN model and an SVM with a radial kernel using only the EIs as variables. The training observations ranged from 3 to 6 observations per class, with the remaining observations allocated to the validation data. The experiment per each training size was run 100 times.

For the HILT model, classes were combined to form 2 meta-classes. Then an SVM with a polynomial kernel was built on the training data and verified using the validation data. This process was repeated until all of the classes were classified alone. Only 2 variables were used for a given pair of meta-classes. This series of binary classification problems forms a decision tree. The training data was composed of 113 observations, while the validation data had 1887.

3 Results

Table 2: Table shows overall mean accuracy results for each of the machine-driven models. The number of observations in each of the training data set classes is provided in the column header. Note that in all training size settings except 3, the SPEI-based SVM model outperforms the CNN model on the validation data.

Model	3	4	5	6	Data Set
CNN	0.98	0.92	0.90	0.84	Train
SVM	1.00	1.00	1.00	1.00	Train
CNN	**0.73**	0.72	0.74	0.74	Valid
SVM	0.70	**0.75**	**0.80**	**0.85**	Valid

A summary of our results and a comparison to a CNN-based approach is provided in Table 2. Our approach has a mean outperformance rate across each classes' of about 5.76% for our SVM model using only EIs. We also compare our HILT model to other approaches in Table 3. Our approach has a mean outperformance rate across each classes' of about 95% for our HILT model.

4 Discussion

The machine-driven SVM model was able to outperform the CNN-based approach by about 5.76%. Our HILT model was able to outperform other approaches by about 95% on average. Thus, our approach was able to outperform the other models for pill shape classification.

Table 3: Table with the mean precision (MP) values for various models. The first and third rows correspond to the model name. The second and fourth rows correspond to the MP values. The first to third models were SVMs with polynomial (SVM - P), radial (SVM - R) and sigmoid (SVM - S) kernels. The fourth model is an Naïve Bayes (NB). The fifth model is a linear discriminant analysis (LDA) model. The sixth model is the HILT adaptable tree built by Maddala *et al.*(Maddala). The seventh model is the logistic regression (LR) built by Maddala *et al.*(Maddala - LR). The eighth model is our HILT tree described in this manuscript (Lamberti).

Model	SVM - P	SVM - R	SVM - S	NB
MP	0.355	0.757	0.269	0.623
Model	LDA	Maddala	Lamberti	
MP	0.801	0.897	**0.990**	

5 Conclusions

Our models provide competitive results compared to other methods. We believe that this is in part due to the inclusion of EIs and SPs as interpretable features. Future work would improve the model to obtain a higher classification rate and remove the HILT components.

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