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PetFinder Adoption Prediction

– ITSG report –

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Abstract

This paper presents an intelligent system designed to aid pet adoption by providing information about certain animals to caretakers and also to people looking for a pet. One can search through all the available pets in the system and find out the best fit for him, based on its characteristics and also on its adoption chances, which the system can predict using machine learning algorithms (tree-based algorithms, multilayer perceptron, convolutional neural network). Specifically, the system can find the least "popular" animals, raise awareness for people and help caretakers focus on the animals that need it more.

The first chapter of this paper focuses on obtaining a reliable algorithm that can predict the "adoptability" of an animal based on its characteristics, description and pictures. The scientific problem was approached by using supervised machine learning. Training the algorithms required a robust, labeled dataset, provided by PetFinder.my, Malaysia's leading animal welfare platform since 2008, with a database of more than 150,000 animals - https://petfinder.my.

The second chapter shows the related work that was taken in this direction and the results obtained by others, most of them shared by the participants at an online competition held on the Kaggle platform, called PetFinder.my Adoption Prediction [14]. It also presents useful tools in solving the given prediction problem.

The third chapter focuses on several approaches, which were implemented and compared during this research, for the final solution to be chosen and then integrated into a web application.

The fourth and final chapter presents a an application demo, both we and mobile, which uses the best solution found during this research, with a minimalist approach.

TODO: 1. la cnn descrierea 2. recitita ca sunt greseli 3. la functionalitati revizuit (trebuie poze cu aplicatiile) 4. filmare aplicatie

Contents

Chapter 1

Introduction

1.1 Problem Overview

Thousands of homeless animals in the world need a family to adopt them. While many of them live in shelters all their life, others are euthanized and only a few of them end up finding a family willing to adopt them. However, in recent years, adoption has increased and many people have found a pet friend inside shelters, offering it a second chance. The aim of this work is to further increase the adoption rate by proposing an intelligent instrument that can work with centralized data of animals living in shelters, do a smart analysis of their real chance of adoption and provide useful information to the caretakers and also to people looking for a pet. In other words, the adoption system uses an intelligent approach when examining the animals, by learning to predict the chances of a pet to be adopted, in order to improve the work of animal shelters.

1.2 Paper structure and original contributions

The main focus of this paper is finding a viable solution based on machine learning algorithms that can predict the adoption speed for an animal with a high degree of accuracy. Another important step is integrating the final solution into a user-friendly application so caretakers and also people will be willing to adopt an animal easily, with access via the internet.

The paper is structured in chapters as follows:

- The first chapter focuses on obtaining a reliable algorithm that can predict the "adoptabil-

ity" of an animal based on its characteristics, description and pictures, by using supervised machine learning.

- The second chapter talks about related work, results and useful tools in solving the research problem.
- The third chapter focuses on several approaches, which were implemented and compared during this research and on the final solution which was then integrated into an application.
- The fourth chapter presents the intelligent system as a whole, focusing on the integration part and the client, a web application which uses the best algorithm which can predict the "adoptability" of an animal. The functionalities are presented here, together with the use-cases aimed to both caretakers and people looking for a pet.

Besides, in terms of contributions to the scientific problem, the main point is the implementation of an intelligent algorithm for solving the problem of predicting the adoption rate of rescued animals (i.e., the adoption speed - a value between 0 and 4). Specifically, supervised machine learning is used on a large dataset containing information about pets, which was collected by PetFinder.my, Malaysia's leading animal welfare platform since 2008, with a database of more than 150.000 animals - https://petfinder.my. The experiments reported in this paper were conducted on different machine learning models, such as convolutional neural networks, multi-layer perceptrons and tree-based algorithms, using different architectures and tuning the models in order to find the best algorithms. Also, combining the power of these models was taken into consideration in order to obtain predictions as accurate as possible.

Moreover, the second contribution of this report consists in building an intuitive, easy-to-use and user-friendly software application.

Chapter 2

Related work and useful tools

2.1 Related work

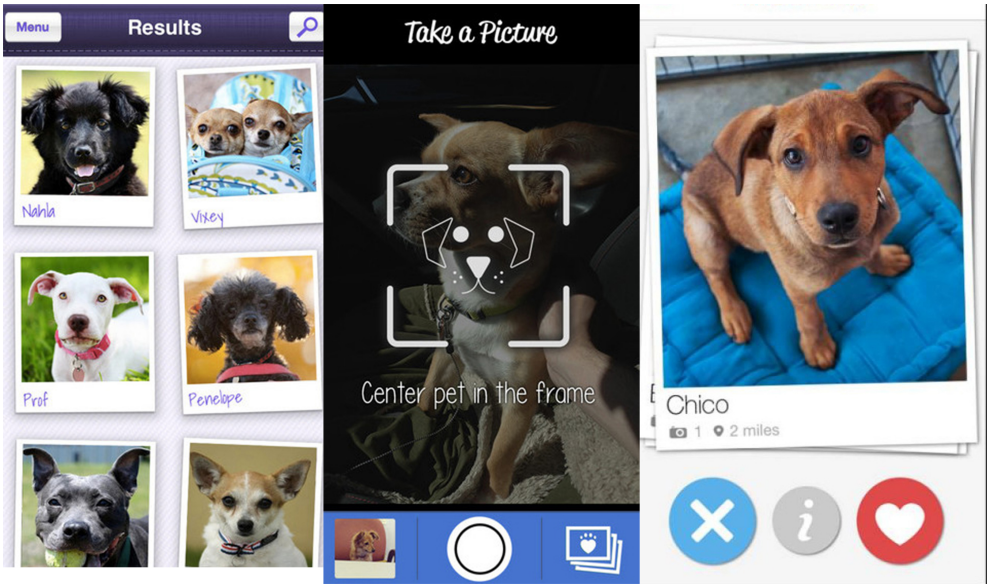
Thanks to the fact that the number of pet lovers are constantly increasing, the society fashion and city administrations as well, provide more opportunities for us to have a comfortable life with our beloved pets. As for the chances of people adopting and keeping pets in their life is increasing as well. Therefore, the internet adapting to the newest trends, now has incomparably more information and together with that, many applications specialized in this field.

As of the purpose of our platform, we support the adoption over continuous breeding as long as there are orphan pets waiting for a loving parent. Considering that our initiative is not new, nor shocking to exits, we researched the domain a bit and found several applications, more or less complex, but with similar target as ours: adopt the perfect furry new family member.

For a better overview, we list the most closely related applications found, summarize and compare the functionalities with our vision.

First in the list, **Petfinder** is one of the applications that stand out more, due to their provided data. Owners of not only a website, but nowadays a mobile application as well, their main methodology is filter based search with a customer friendly interface. Main reason of our highlight, is their founded research of data mining projects, which provided us and many others with our current database of pets and their properties. Therefore, our goal and their goal is aligned, by creating an AI, based on their data, and find out as accurately as possible which pet is more likely to be adopted.

Their problem, as I already specified earlier, is listing the possible pet candidates, based



on different filters, such as location, breed, and others. Our solution wants to improve similar concepts further, by using our learning patterns and therefore showing the most likely adoptable pets, and drawing attention toward pets with a low scored profile as well.

Secondly placed, **LikeThat Pets**, is the application which when it comes to good ideas of how to use up artificial intelligence best, takes the lead. *The application allows you to take a photo of a dog or cat, and with the help of recognition technology, it will generate similar pets for you which are up for adoption* [1] . Almost like a facial recognition application, built for pets, it is a filtering method raised to a completely different level. Although, our problem might look highly different, both looks for most likely adoptable features, one at a user level, while our at a general level. While LikeThat Pets filtering can be considered very strong and discriminating, our method will give more chances to any pet up for adoption, balancing the adoptability percentages with listing both highly ranked pets and lowly ranked pets head to head, raiding awareness of no discrimination between any pet in need, but also taking in account user needs and preferences.

And last but not least, **BarkBuddy**, the tinder for pets and owners looking for a pet. Although no smart learning is present in the background, what our solution focuses more one, their preference based application can be a very good start for a future improvement towards pet adaptability. The left-right swiping when it comes to a pet you prefer or not, gathers good data about the properties of pets which are more "liked". The issues and problem they have is similar to, the earlier mentioned, Petfinder application, but with a different interface. Our

application and idea, can be considered an impovement in the same ways, it can be considered for Petfinder app.

2.2 Useful tools

In order to build, deploy the models and build the web application, several libraries, IDEs and other tools were used:

- Jupyter Notebook - As data science environment
- scikit-learn - Python machine learning library [17]
- Tensorflow - Machine learning library [19]
- Keras - Python neural-network library [18]
- Flask - Web application framework used to deploy the models
- React, React Native - Front-end framework used to build the web client and the mobile client, respectively

Chapter 3

Scientific Problem

3.1 Problem definition

In the current case, the scientific problem which needs to be studied and solved before building the software system that could improve the speed of adoption in animal shelters concerns the prediction of the adoption rate of rescued animals. Supervised machine learning can be used in this case, using the labeled dataset provided by the PetFinder.my platform mentioned earlier and published on the Kaggle AI platform [14].

3.2 Input data

The dataset contains two subsets - train and test data, presenting information about 14993 and 3948 pets respectively. Data about each pet is stored in different formats: tabular files, JSON format (for image metadata and sentiment analysis) and image data.

The dataset consists of:

- basic features of different pets - categorical (nominal, ordinal) and numeric (age, quantity, fee, video and photos amount).
- sentiment metadata extracted from the available descriptions for each pet using the Google Natural Language API [16]. It evaluates characteristics such as the power of sentiment for a certain description, using the score (i.e., the emotional leaning of the text - a normalized value between -1 and 1) and the magnitude (the overall strength of

emotion).

- image data - extremely diverse, present in two forms: multiple raw images for each pet, available in different sizes and image metadata, extracted using the Google Vision API [15]. The metadata includes dominant colors and details about objects recognized in the images.

For a more detailed overview of the dataset, we decided to create a mind-map illustrated in the **Figure 3.1** below, with the exact categories from the categorical features, image processing and sentiment metadata.

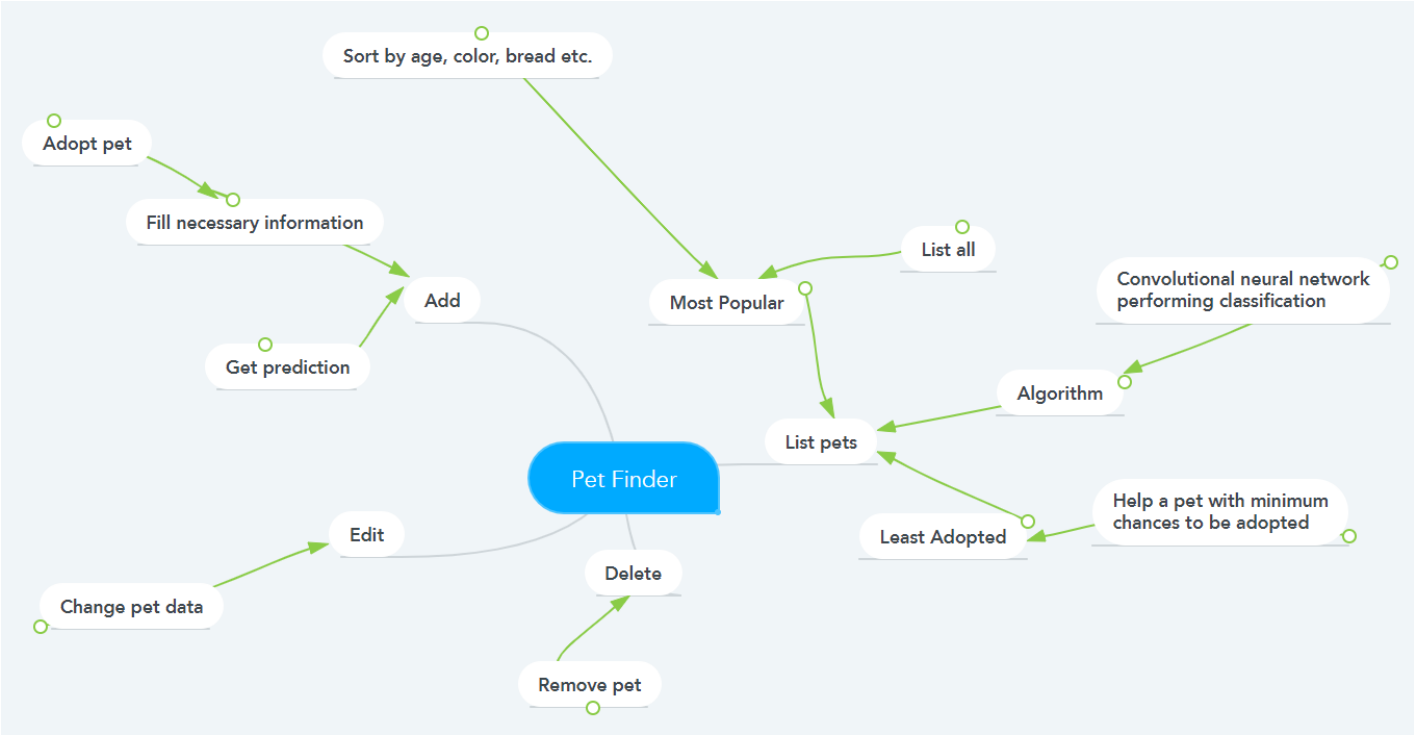


Figure 3.1: Data-set MindMap

3.3 Output data

The problem of predicting "adoptability" can be reduced to a value between 0 and 4, representing the categorical speed of adoption for a pet. In this case, lower is faster, meaning that animals having value 0 have the highest chances of being adopted.

Chapter 4

Proposed approach

Our proposed approach is described in the next subsections, with step by step guide of how our algorithm processes the data. Code snippets and numerical results are attached for more intuitive understanding and testing proofs.

4.1 Data pre-processing

Like any real-world data, the dataset we chose to work with was unstructured, massive and likely to contain errors. In order to assure high quality of the data, pre-processing steps were compulsory in cleaning and transforming it.

4.1.1 Strategies and techniques

The techniques that were used in the pre-processing stage are the following:

- **Data integration:** Data from various resources (i.e., basic features, sentiment data, image metadata) was combined. In this process, a lot of attention was given to object matching and redundancy. As a result, the final input that was fed to machine learning algorithms was contained inside one large CSV file containg 60 features.
- **Splitting up the data:** The dataset was split into training (80%) and testing data (20%) to be able to evaluate how the models perform with unseen data.

- **Normalization:** Normalization of numerical attributes was performed using the scikit-learn library in order to make sure that every attribute has an equal impact in the prediction.
- **Text mining:** Splitting up the description feature enabled the creation of new features, which were fed to the Google Natural Language API [16].
- **Aggregation:** Applying statistical mean, sum to existing features contained in the sentiment dataset to obtain new features (e.g., doc_score_Mean, sen1_score_Mean, sum_mag_Mean).
- **Attribute subset selection:** The dataset was reduced by removing certain features (e.g., sentiment related features) in order to test how different models perform on a smaller subsets of the data.

4.1.2 Image pre-processing

Image pre-processing included mainly image resizing before feeding the images to learning algorithms, such as convolutional neural networks. This step was necessary to reduce computation complexity, taking care to preserve the relevant details from the image.

4.1.3 Feature Engineering and Feature Importance

Moreover, before feeding the data to a model, an essential step was done, namely feature engineering. Large majority of models performed better when using the additional extracted data. An essential contribution to new features came from the sentiment and image metadata. Regarding the image metadata, since some pets have more than one picture, the sum and the average of the scores were computed as new features, setting them to 0 for those who do not have pictures at all.

Additionally, feature importance has been analysed using algorithms such as random decision forest. As shown in **Figure 4.1**, as a result the top 15 most impacting features are: Rescuer, Score, Age, Abundance of specific colors in the picture and other features obtained by aggregation of sentiment data.

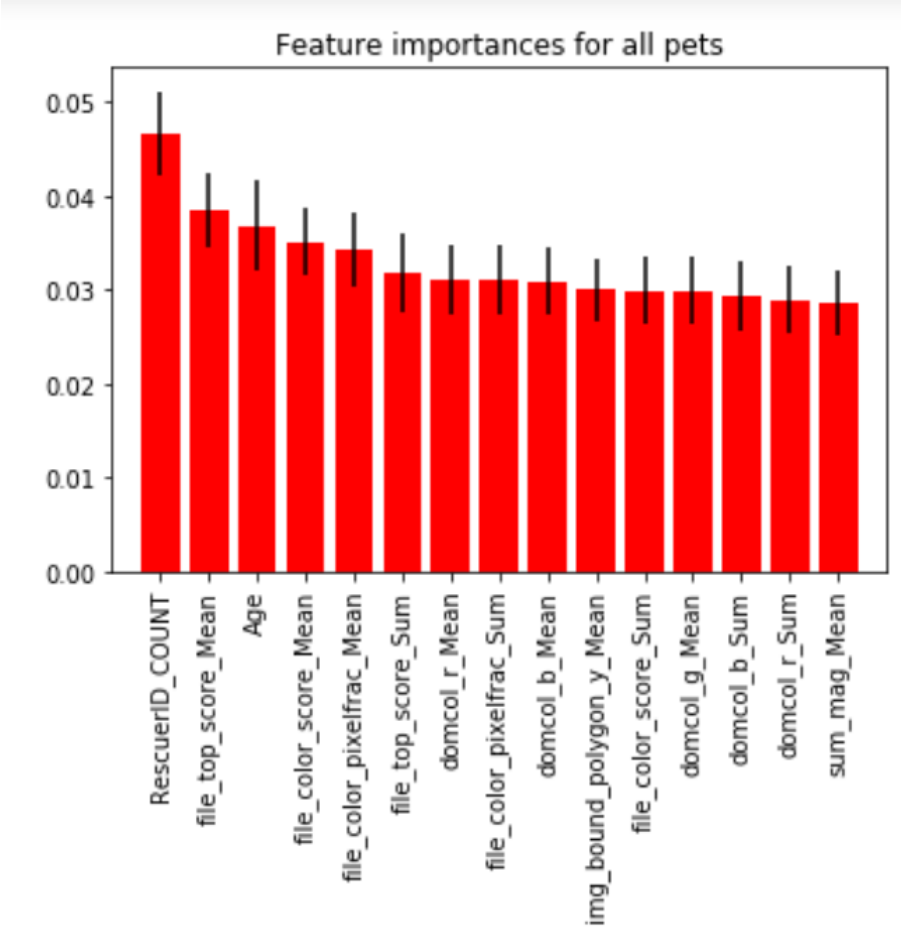


Figure 4.1: Feature importance Top 15

4.2 Models Built

Several models using different machine learning algorithms have been implemented using libraries such as scikit-learn [17], Tensorflow [19] and Keras [18], trained and tested, both locally and on Kaggle. Among the models tested, there were: Multilayer Perceptron Classifier, Convolutional Neural Networks (regression and classification approaches), Random Forest Classifier, K-Nearest-Neighbor, Support Vector Machine.

- **K-Nearest-Neighbor (KNN)**: is an effective and simple but not so much efficient sample-based lazy machine learning approach. The algorithm classifies objects into predefined majority classes of sample members that were created by machine learning. K-Nearest Neighbor searches for the most similar object from the samples with the Euclidean distance which calculates the distance of two vectors [2] [3].

  The benefit of this method is, that it does not require the use of training data to perform

classification. The training data is kept in memory for later testing or validation. Also, it produces valid and valuable results compared to other algorithms with the right mix of prior knowledge. But there are some disadvantages, too. The complexity of its sample similarity computing is huge, so a lot of processing power is needed. In addition, the K-Nearest-Neighbor performance is easily affected by noisy samples and K-NN does not build the classification model itself [4].

In order to create the model, the **sklearn** library, the **KNeighborsClassifier** class was used.

- **Random forest:** is a supervised machine learning algorithm that is capable of both regression and classification tasks. The RF builds up multiple de-correlated decision trees.

  In order to create the model, the **sklearn** library was used, both with classification and regression approaches (RandomForestClassifier, RandomForestRegressor).

- **Support Vector Machine:** is a supervised machine learning algorithm that is capable of regression and classification tasks. The support vector machine builds a hyper-plane, which can be used for classification and is good for finding the boundary to separate different groups and maximize the margin. The goal is to choose the hyper-plane with the highest margin between the hyper-plane and the training set [8] [9].The benefit of the support vector machine algorithm is its effectiveness in high dimensional spaces and its ability to have different kernel functions for various decision functions. Furthermore, it has a good accuracy and works well on smaller cleaner datasets. A disadvantage of the support vector machine is, that it isn't working as well on large datasets due its high training time. It also has a lower effectivity on noisier datasets with overlay classes [10].

  In order to create the model, the **sklearn** library was used, specifically the SVC class, for support vector classification. To optimize the model further, parameters can be optimized to find the best performing values.

- **Multilayer Perceptron:** is inspired of the structure and functional aspects of the human brain (especially how brain neurons work) and uses this to develop algorithms that can model prediction problems and complex patterns.The algorithm is based on an input layer, multiple hidden layers and an output layer. Each layer consists of an interconnected

group node, which is usually connected in a feed-forward way and afterwards is trained based on a back-propagation algorithm. The benefits of ANNs are the ability to model complex and nonlinear relationships, making them very useful on real life data. After a successful training, the algorithm will learn to generalize, so it can perform on unseen data. [11]

The sckit-learn library, specifically the MLPClassifier class, was used to build a multi-layer perceptron classifier. The model was further tuned until it achieved good enough results.

- **Convolutional Neural Network (CNN):** The convolutional neural network was implemented using the Keras Sequential model, which consists in a linear stack of layers. After initialization, the architecture of the convolutional neural network was modeled by adding specific layers, via the add() method.

  The first layer in the convolutional neural network is a two-dimensional convolutional layer (2DConv), which extracts feature maps from the input. The input shape consists of 64 x 64 RGB images (frames), having 3 channels. It performs spatial convolution over images, using 20 different output filters, and a 3 x 3 sized kernel (or convolution window), with a 3 x 3 stride, setting the step or the space between each sample. The ReLU element-wise activation function is applied to the outputs, setting all negative pixels to 0.

  The second layer represents a pooling layer, more specifically a two-dimensional max pooling layer (MaxPooling2D), with the pool size of 2 x 2 and a stride of 2. It is used to reduce the spatial dimensions of the rectified feature value, by taking the largest element at each step. Hence, only the most important, relevant features will be retrained, overfitting is avoided and the network will become less sensitive to small distortions in input.

  The third and fourth layers reproduce the previous structure. A convolutional layer with size 3 x 3 for the kernel and strides and the ReLU activation function, followed by a max pool layer with size 2 x 2 for the pool dimension.

  The feature learning process ends with the flattening layer, which flattens the 4D input, without affecting the sample/ batch size. The output will be a vectorized version of the last pooling layer. After this operation, the classification process may take place. The network contains two fully connected layers (or densely connected) for the classification

task. For the first layer, the output space or the number of units is 128, with a ReLU activation function and the last layer contains one unit, 128 learnable weights, with a sigmoid activation function. It will contain the output, as well as the class scores.

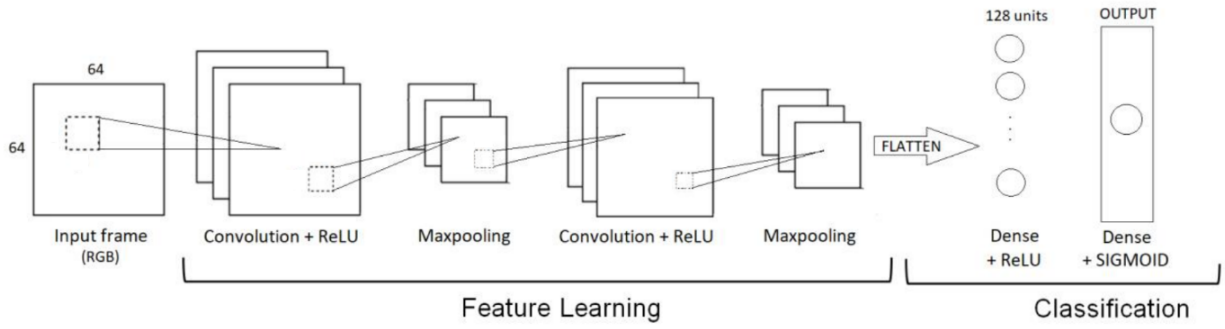


Figure 4.2: CNN layers

4.3 Model evaluation

After the construction of a model based on training data, we started to evaluate the performance of our model on test data In the evaluation process, various performance measurements were used, such as accuracy, precision, recall and F1-score for classification and mean absolute error, R-squared for regression. The measurements are introduced in detail below:

(1) Accuracy and error rate: Models are evaluated by looking at correctly and incorrectly classified instances. Focus on the predictive capability of a model using confusion matrix.

$$accuracy = \frac{TP + TN}{TP + FP + FN + TN}$$

$$Error\ rate = 1 - accuracy$$

(2) Precision p is the number of correctly classified positive examples divided by the total number of examples that are classified as positive.

$$p = \frac{TP}{TP + FP}$$

(3) Recall r is the number of correctly classified positive examples divided by the total number of actual positive examples in the test set.

$$r = \frac{TP}{TP + FN}$$

(4) F1-Score combines precision and recall into one measure

$$F1 = \frac{2pr}{p + r}$$

$$F1 = \frac{2}{\frac{1}{p} + \frac{1}{r}}$$

4.4 Models and results

4.4.1 Model comparison and final choice

As a result, after several experiments using different subsets of the training set, tuning the parameters of the models and trying different neural network architectures, the best model was the convolutional neural network performing classification. Models were tested on both the full dataset and also using various subsets, containing the best 15/20 features. The difference in score was not significant. As a result, further work was made using the entire dataset.

The table below shows the results of the evaluation using the entire set of features for tree-based algorithms and multilayer perceptron, respectively the raw images as input for convolutional neural networks.

Considering the numbers obtained, **Figure 4.2** shows algorithms that performed well, as well as algorithms that were no better than random. Accuracy scores ranged from 48% to 80%, precision scores from 43% to 64% and recall scores from 42% to 53%. F1 score was used in the evaluation process. According to the accuracy and F1 score, the Multilayer Perceptron (MLP) achieved the best result among all the classifiers, with over 50% score, whilst the other performed way under.

Since one of the targets was to also be able to intelligently analyse the uploaded pictures of pets as well, a convolutional neural network algorithm was also used to determine the adoptability. As shown in **Figure 4.2**, it performed even better than every other model, obtaining 80% accuracy on the test data.

	Accuracy	Precision	Recall	F1 score
SVM	0.486	0.482	0.404	0.464
Random Forest classification	0.527	0.432	0.437	0.424
KNN	0.534	0.54	0.447	0.438
MLPClassifier	0.65	0.64	0.543	0.538
CNN classification	0.8			

Figure 4.3: Performance of the Classification Models

	MAE	R^2
CNN regression	0.07	0.179
Random Forest regression	1.72	

Figure 4.4: Performance of the Regression Models

Regression models were implemented as well, but due to the lack of acceptable results, as shown in **Figure 4.3**, we decided to opt them out and continue the research focusing on the MLP and CNN classification algorithms.

4.4.2 Results

Eventually, we conducted several experiments on our best performing models, the multilayer perceptron and the convolutional neural network. The models were integrated using a Flask web application and exposed to clients via REST services.

After running the predictions using the models separately and together,the results obtained were slightly different. The algorithm used when combining the models computed the average sum of the predictions of the MLP classifier (taking 55 text features as input) and the CNN classifier (taking raw images as input).

The results presented below show the difference in the results obtained either by using the prediction from the MLP classifier, respectively the CNN classifier, or a combination of these two models (the average sum).

The following input data was used for the MLP classifier, containing 55 pet features in total:

```
{
  "Type": "2",
  "Age": "6",
```

```
  "Breed1": "265",
  "Breed2": "0",
  "Gender": "1",
  "Color1": "4",
  "Color2": "7",
  "Color3": "0",
  "MaturitySize": "2",
  "FurLength": "2",
  "Vaccinated": "1",
  "Dewormed": "1",
  "Sterilized": "1",
  "Health": "1",
  "Quantity": "1",
  "Fee": "100",
  "State": "41326",
  "VideoAmt": "0",
  "PhotoAmt": "6.0",
  "img_bound_polygon_x_Mean": "318.5",
  "img_bound_polygon_x_Sum": "1911.0",
  "img_bound_polygon_y_Mean": "478.5",
  "img_bound_polygon_y_Sum": "2871.0",
  "img_confidence_Mean": "0.79999995",
  "img_confidence_Sum": "4.7999997",
  "img_imp_fract_Mean": "1.0",
  "img_imp_fract_Sum": "6.0",
  "domcol_r_Mean": "192.16666666666666",
  "domcol_r_Sum": "1153.0",
  "domcol_g_Mean": "148.33333333333334",
  "domcol_g_Sum": "890.0",
  "domcol_b_Mean": "151.16666666666666",
  "domcol_b_Sum": "907.0",
```

```
  "file_top_score_Mean": "0.9401869822222223",
  "file_top_score_Sum": "5.641121893333334",
  "file_color_score_Mean": "0.0712560363",
  "file_color_score_Sum": "0.4275362178",
  "file_color_pixelfrac_Mean": "0.05002673512033334",
  "file_color_pixelfrac_Sum": "0.30016041072200006",
  "file_crop_conf_Mean": "0.79999995",
  "file_crop_conf_Sum": "4.7999997",
  "file_crop_importance_Mean": "1.0",
  "file_crop_importance_Sum": "6.0",
  "pic_no": "3.5",
  "doc_score_Mean": "0.7000000000000001",
  "sent_count_Mean": "4.0",
  "sen1_magnitude_Mean": "0.0",
  "sen1_score_Mean": "0.0",
  "sum_mag_Mean": "2.6",
  "sum_score_Mean": "2.6",
  "doc_mag_corr_Mean": "0.7000000000000001",
  "sum_mag_corr_Mean": "0.65",
  "has_eng_description_Mean": "1.0",
  "RescuerID_COUNT": "2",
  "PureBreed": "0.0"
}
```


Also, the image data, fed to the CNN classifier consisted in several pet images. The following sample was used for this experiment:

- **Feeding the algorithm a raw pet image:** This approach resulted in the adoptability value 3, which means the chances of the animal to be adopted are low. The model used in this case was the CNN classifier.
- **Feeding the algorithm textual features:** The adoptability value was 1, meaning the same pet is given high chances of adoption when analysing its textual features, containg

Figure 4.5: Pet image sample

basic features, such as gender, age, breed, color etc.), and extracted features (from both description and image metadata). Given the fact that the MLP classifier is fed with very different data, based on analyzing text, and words, the difference in classification compared to the CNN classifier is justified and expected. The input is given in JSON format, as an object, containing 55 pet features, also shown above.

- **Feeding the algorithm both textual features and raw image data:** As the algorithm that combines the two different models based on neural networks uses the average sum, the result was an average between the two results, specifically 2. We chose equal weights for the models considering the fact that they both work with different kinds of data, hence it is not very relevant to compare their accuracy and assign a larger weight to the best performing model.

Chapter 5

Application

5.1 Functionalities

The application provides and plans to provide several functionalities, creating the chance for the people to find the right pet and also for the pets to find the right owner.

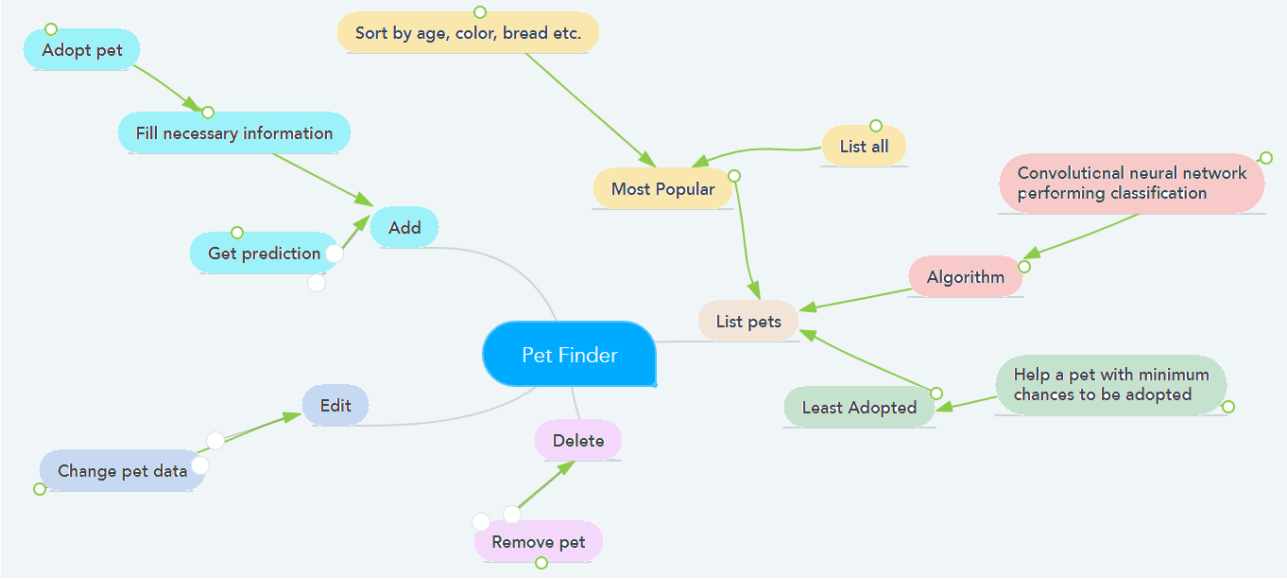


Figure 5.1: Introducing only features

As shown in the **Figure 5.1**, we plan on having functionalities as follows:

- Add pet: The platform provides minimalist forms to complete the pet information and upload an image. As mentions before, it now only provides manually JSON introduction for the desired features, which will be worked on in the future for a more user-friendly

approach - *more information provided in* ***Chapter 6***. Through adding a pet, we would like to see how adoptable it is so we can make positive changes as soon as possible, that is why we also added as an **additional feature** the c*compute adoptability* feature.

- **List pets:** The app provides a list with non-adopted pets. Future development in this are will be done like filtering or recommending pets - *more information provided in* ***Chapter 6***.

- As **additional features**, we added easy manageability to the application for application owners and clients, them now being able to delete and update the already uploaded pet information as well.

As illustrated in the **Figure 5.2**, our application is in demo stage, serving the purpose of pure testing and simple client presentation. Plannes are for future development - *more information provided in* ***Chapter 6***.

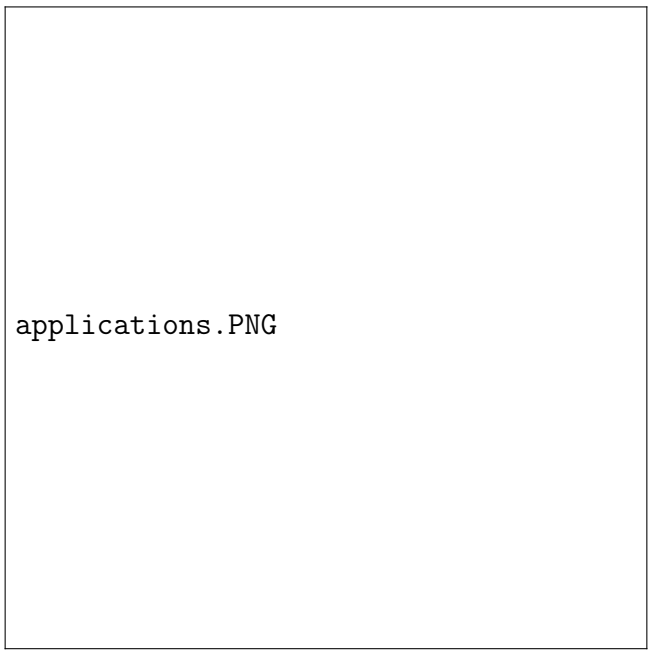


Figure 5.2: Web and Mobile applications

Chapter 6

Conclusion and future work

6.1 Future work

Developing the basic logistics of an application will be the core part of a project, but without smaller features and proper UI, its value will decrease to zero. Therefore, as future development, there is still plenty to do. As for important futures to be developed in the future, we considered the followings:

- **Authentication:** One of the functionalities is the registration / authentication, which requires the basic details of the user in order to find to be able to proceed with the adoption of a pet. It can be crucial for pet adoption, since having a profile will increase the possible future enhancements of the artificial intelligence behind, recommending personally-knotted pets to adopt for each user. Also has the potential of creating lists and therefore keeping track of your favorite pets so far.

- **List pets enhancements:** The app shall provide a list with non-adopted pets, which can be sorted by age, color, breed and some other criterias in order for the user to be more easily to choose the right pet.

- **List most adoptable pets:** The application shall also provide a list with the most adoptable pets, being sorted by the adoptability score criteria, making the decision easier for the people not sure about which animal to adopt.

- **List least adoptable pets:** We shall also provide a list with the pets having the least

chances for adoption, which are the pets with the smallest adoptability score, helping the people who want to help a pet with special needs, ready to take risks.

- **Adopt a pet:** We also shall have a functionality that help the user to adopt the desired pet, handing all the details that the user needs to know in order to proceed with the application for the adoption.

- **Other user-interface enhancements:** The application shall be simple and user-friendly, following the modern design standards to make it more appealing to the eye, easier to use and therefore more attractive to a large group of people.

6.2 Conclusion

As a conclusion, our application has achieved a proper testing phase, with reliable results. With the above analysed model scores and adoptability tests, we can say that the hard path has been stepped out, and only refinements to come. The application is in a good state for testing, but requires additional work towards a more desirable appearance and usage transparency.

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