AutoFold

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***Abstract*—As automation of everyday tasks become more common, it is inevitable that the traditional task of folding clothing by hand will be replaced by automated laundromats. Automated clothing identification and folding not only promises to significantly speed up this traditionally slow process, but can also streamline the entire laundry process. This project aims to solve two aspects of this problem, clothing identification/classification and detection of folding lines. In order to do this, we introduce a convolutional neural network trained on real images for clothing identification/classification and a traditional edge detection approach for folding line detection. We evaluate our convolutional neural network through its ability to identify real world images and compare the best architecture for doing so. Furthermore, we use our folding algorithm on several different real world images to visually show its ability to find folding lines as a human would. Our neural network shows promising results but requires further improvements to attain acceptable accuracy while our folding algorithm is able to achieve good results, showing that with further refinement it could reliably determine patterns for automated folding.**

***Index Terms*—Automation, Machine Learning, Edge Detection, Folding, Laundry**

I. Introduction

With the automation of everyday tasks becoming more prominent, automated laundromats will undoubtedly be commonplace in the future. Traditionally, the folding of clothing has been done by humans by determining the type of clothing and then following one of the various folding methods for the article in question. However, folding clothing by hand is not only inefficient, but does not scale well to large operations like a laundromat.

By utilizing the many images of clothing available online through the e-commerce industry, a machine learning model can be trained to identify clothing. Once the article is identified, an edge detection algorithm can be utilized in order to identify how to fold the article of clothing.

This project investigates some steps needed in order to develop a fully automated folding station for a laundromat. It first examines how to utilize a convolutional neural network in order classify articles of clothing. A subset of Fashion Product Images (Small) [1] is used for training and testing the network. The system is evaluated on these images to determine the network's accuracy, precision, and recall compared to the included labels. The project then uses an edge detection approach in order to determine folding lines given an article of clothing and its determined class. This folding algorithm is designed to be hardware ambiguous so it can be incorporated and expanded to other possible implementations, without requiring intense computational power.

II. Related Work

There currently exists research into clothing classification using neural networks, which show some promising results with their corresponding datasets. Within the area of folding methods, most research is focused on automated folding methods for home use. The most advanced of these are closed source commercial projects, but there exist some research projects in this field. These research projects suffer from being limited in scope, working only on t-shirts, or having size limitations.

One of the most notable projects of relevant clothing classification is FashionNet and the corresponding dataset DeepFashion [2]. DeepFashion is a large dataset of several hundred thousand images collected from various e-commerce sites developed for research into the area of clothing identification and classification. The team that developed DeepFashion also made a corresponding neural network for working with the dataset, FashionNet, but this neural network is not publicly available. While this neural network and dataset show promising results, the closed source nature of FashionNet and our hardware limitations meant we could not expand on this work for our project, and instead chose to use the Fashion Product Images Dataset [3] along with a publicly available neural network architecture as a starting point.

Within the area of closed source commercial projects for folding, there currently exist two notable designs. The first of these designs is a prototype still under development called Foldimate [4]. This project is designed as a standalone unit for home use which accepts an article of clothing and then folds it according to user preferences and clothing type. The user feeds in the clothing one article at a time and the machine folds each article before depositing it into a pile. This machine automates the physical folding process but still requires constant user input to receive the clothing. Being a commercial closed source project that is still in the prototype stage, it is difficult to further analyze the methods the machine uses as the company only says it uses a robotic system. The other commercial project found in this area is the Automatic Folding Machine FX-23 by Thermotron Textile Machines [5]. This is also a closed source machine and appears to work similarly to the Foldimate. However, it can also prepare clothing for bagging while being designed for a more industrial setting than Foldimate.

One publication that attempts to create a way to automatically fold t-shirts is the Automatic T-Shirt Folding Machine by Shetye, Randive, and Shedbale [6]. This publication creates a mechanical system using motors in preset positions which are time controlled to fold t-shirts in a predefined 8 step method. The goal of this system is to make folding clothes at home much more efficient and requires the user to place one t-shirt on the machine at a time and then to operate the machine via a push button. Another publication is the Cloth Folding Machine by Yiwei Liu, Dung Tran, and Ray Wang [7]. This publication uses a series of mechanical gears driven by electric motors to move boards that fold the clothing placed on top of the machine. It is able to fold both t-shirts and pants but requires manual switching of patterns in order to do so and the authors note that it is not able to achieve a good shape for the final folded clothes. Both of these publications suffer from only being able to fold a limited number of clothing styles and require constant user input. This makes them unsuitable for industrial use despite providing significant advantages over manual folding for home use.

While the above examples all provide ways to fold clothing, they suffer from being either limited in scope and requiring significant modifications for expanded capabilities, or being closed source software that cannot be modified to suit a particular use case. Additionally, these methods seem to be dependent on user input, with no system in place to identify the clothing and select the appropriate folding technique automatically. We aim to solve these issues by providing a generic open source algorithm for identifying clothing and determining appropriate folding techniques that can be both easily expanded for unique business cases and adapted to numerous types of hardware.

III. Methodology

A. Overview

This project aims to show solutions for 2 aspects of the process needed for an automated laundromat: identifying clothing, and determining fold lines in preparation for folding. We solve the first problem of identification through the use of a convolutional neural network. Subsequently, we propose solving the second problem of identifying folding lines by using a traditional edge detection approach.

In order to accurately identify different classes of clothing, the neural network must learn the differences in shape, sleeve length, collar type, and other aspects of clothing. To perform this training, we use a subset of the Fashion Product Images (Small) [1] dataset. This dataset provides 44,441 different professional images of clothing along with corresponding labels. Initially, we trained the neural network to classify the subset of clothing labelled as jeans, shirts, and dresses.

With respect to determining how to fold clothing, we propose a traditional edge detection approach. We use the larger version of the dataset used for the neural network [3] in order to better visualize the results. This approach utilizes the edges of the clothing and a sliding window in order to determine lines defining the sides of the article of clothing and then uses a predetermined offset to decide where the clothing should be folded. As an initial demonstration of this approach, we demonstrate it on images of t-shirts from the Fashion Product Images Dataset using two folding methods, a "sides-in" technique and a "quarters" technique. The "sides in" technique results in the chest of the shirt being on top as is commonly seen in stores, while the "quarters" technique is the simpler method more frequently used in homes.

B. Neural Network Classification

In order to determine the best network for classifying the different classes of clothing, we tested several different network configurations. Initially, we began with a simple network given by Tensorflow [8] that consists of two convolutional layers, with the first layer having 64 outputs and the second layer 32 outputs, feeding a 256 node fully connected layer and a final fully connected layer for determining the classes. It utilizes the relu activation, defined in (1), for all layers except for the final layer which utilizes softmax, defined in (2) for classes $i = 1, \ldots, K$ and scores $\mathbf{z} = (z_1, \ldots, z_K)$. In order to prevent overfitting, 30% dropout and 2-dimensional max-pooling layers are used after each convolutional layer, with 50% dropout being used after the initial fully connected layer.

$$value = \begin{cases} input, & input > 0 \\ 0, & input \leq 0 \end{cases} \tag{1}$$

$$\sigma(\mathbf{z}) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \tag{2}$$

After several variations of the network, we modified the initial network to use 4 convolutional layers before moving onto data collection. These convolutional layers consisted of 128, 64, 64, and 32 outputs respectively, along with the same 2 fully connected layers described in the initial configuration. The network was further modified to only use a dropout layer after every 2 convolutional layers and a max pooling layer only after the 4 convolutional layers. As in the initial configuration, this network used the relu activations on most layers and softmax on the final layer. Several different optimizers were tested, however all iterations of the network utilized sparse categorical cross entropy loss. Fig. 1 shows a visual breakdown of the convolutional portion of this neural network.

Parameters were then modified in an attempt to improve performance to determine the best network given the Fashion Product Images (Small) [1] dataset. These modified parameters include the number of epochs, the minibatch size, the colour composition, and the weights used for each input class.

C. Folding Line Detection

Due to the clothing within a given class being relatively uniform in shape, such as virtually all t-shirts having an identical shape and therefore folding method to each other, we chose to use a traditional edge detection approach rather

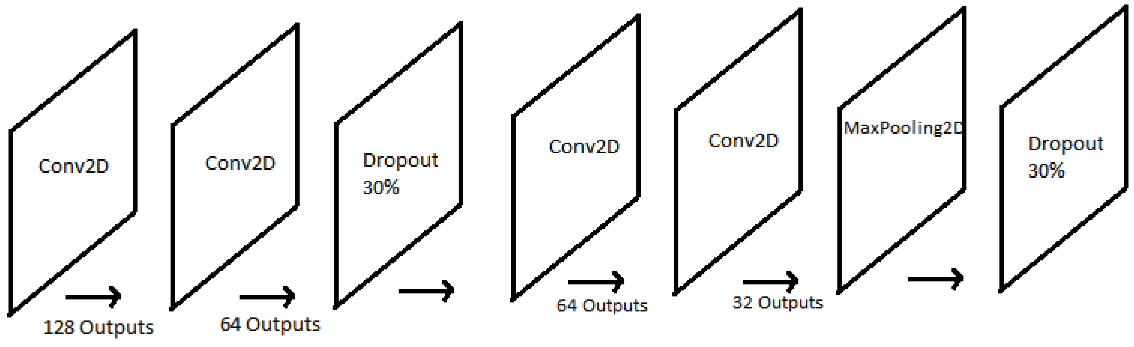

Fig. 1: Convolutional portion of neural network architecture used for classification

than a neural network. By using such an approach, the amount of work needed to expand the algorithm to a new clothing class or to modify the parameters for a particular use case is heavily reduced, and it removes the need to have labeled training data. This approach also means the algorithm can be applied to any image and can be used independently from the neural network classifier described previously if provided with a class.

The algorithm first finds the edges of the article of clothing using the Canny Edge Detector as implemented in OpenCV [9]. This step first removes noise by using a standard 5x5 Gaussian filter, then once noise is removed from the image, the first derivative in the horizontal and vertical directions, $\mathbf{G}_x$ and $\mathbf{G}_y$, are found using a 3x3 Sobel kernel. With this information, the edge gradient and direction for each pixel can be found as in (3) and (4) respectively.

$$\mathbf{G} = \sqrt{\mathbf{G}_x^2 + \mathbf{G}_y^2} \tag{3}$$

$$\theta = \arctan\left(\frac{\mathbf{G}_x}{\mathbf{G}_y}\right) \tag{4}$$

With these values found, the image pixels are iterated over to only retain edge pixels using non-maximum suppression [9]. As a final step, the intensity gradient of each pixel is checked and compared with its neighbours through hysteresis thresholding. Pixels with an intensity gradient greater than a maximum value or that are continuous with neighbour pixels meeting this criteria are kept, while pixels not continuous with a pixel whose intensity gradient is greater than the maximum or that fall below a minimum value are discarded [9]. For this step, we used a value of 125 for the maximum threshold and 50 for the minimum threshold. With all the edge pixels detected, we apply binary thresholding with a value of 127 to the image before detecting continuous edges with OpenCV's findContours function [10]. Next, we calculate the clothing moment in order to determine its centroid with OpenCV's moments function [11], which determines the moment by finding the average of the pixel intensities. The clothing centroid can then be found from the moment as in (5) and (6).

$$C_x = \frac{M_{10}}{M_{00}} \tag{5}$$

$$C_y = \frac{M_{01}}{M_{00}} \tag{6}$$

With the clothing centroid found, we can determine the folding lines for the "quarters" technique, as shown in Fig. 2, with vertical and horizontal lines through the centroid.

In a similar fashion to the "quarters" technique, we can use the same edge detection and centroid techniques to begin the "sides-in" technique. We then remove all smaller contours to remove some noise and split the image into left and right halves. We apply a sliding window to the contour data in order to find the vertical window with the most contour points on each half, which should align with the sides of the shirt. With both sides found, we calculate one quarter of the distance between them to draw our vertical folding lines. Using the horizontal line passing through the article centroid along with these two mid-lines, we have the folding lines for the "sides-in" technique, as shown in Fig 3.

IV. Experimental Results

A. Datasets

In order to train and evaluate the neural network as well as test the folding algorithm, we utilized two versions of the Fashion Product Images Dataset [3]. Due to hardware limitations, we utilized the small images version of the dataset, Fashion Product Images (Small) consisting of 80px by 60px low resolution images [1], for training and evaluating the neural network. As the folding algorithm was not affected by these same hardware limitations, we utilized the larger version for these: Fashion Product Images Dataset consisting of 2400px by 1600px high resolution images [3].

As an initial demonstration of the neural network, we chose to use subsets of the dataset that had clear differences. To this extent, we created two subsets called "Dress-Jeans-Tees" (DJT), consisting of dresses, jeans, and t-shirts, and "Dress-Jeans-Shirts" (DJS), which also consisted of dresses and jeans but contained mostly button-down shirts instead of t-shirts. These subsets contained comparable amounts of dresses and jeans, with 464 dresses and 608 jeans. The first subset had approximately 87% of all images belonging to the t-shirts class for a total of 7068 t-shirts, while the second subset had approximately 75% of all images belonging to the shirts class, with 3215 shirts. Both of these subsets suffered from the dataset having numerous erroneously labelled images, with the DJS subset suffering less from this issue than the DJT subset. We chose to compare the neural network on behaviour on both datasets, to compare the results from a cleaner dataset compared to an occasionally mislabeled dataset. With the DJS subset, we also attempted to create additional subsets in order to evaluate these changes on the neural network by manually cleaning the subset, as well as balancing out the image quantities across classes. Due to the small amount of dresses and jeans available, a balanced subset could only contain 400 images of each category and still maintain enough dresses for testing, which is a small amount for training. An additional dataset was created by manually cleaning the "shirts" category to remove all images that were mislabelled, contained multiple articles of clothing, or contained clothing worn by models. The dresses and jeans classes could not be cleaned in this manner due to the small quantity of images that would remain being insufficient for training and testing.

The folding algorithm does not require training or testing, so images were randomly selected as samples on which to test this algorithm. The t-shirts class was chosen due to its high amount of good quality images while also encompassing all of the steps necessary to fold most other categories of clothing, such as jeans.

B. Neural Network Training

In order to train the neural network, we performed several runs on the different dataset subsets, with each run using a batch size of 4, 6 epochs, and full colour RGB images. For each of the "Dress-Jeans-Shirts" subsets discussed earlier (full, even split and cleaned), we utilized 5 different network weighting schemes in order to account for the dataset imbalance and evaluated their performance. These weighting schemes, with the weights for each category, are shown in Table I. We also tested two different optimizers, Adam and Adadelta, to determine the performance of each optimizer and weighting system on the dataset.

C. Neural Network Results and Analysis

A set of testing images was randomly selected from the subsets on each run in order to evaluate the performance of the network variations. The accuracy score generated is the percent of correctly predicted labels across the entire set of images. We found that the best performance for the "Dress-Jeans-Tees" subset across all networks had an accuracy of 87%. However, this result merely reflects the percentage of t-shirts in the dataset, which is identical. Similarly, the best performance on the "Dress-Jeans-Shirts" subset was 75%, which is also equal to the amount of shirts in the subset. Noting this, we realized the network was overfitting to the most common category which led us to using the different weighting schemes and subsets of the "Dress-Jeans-Shirts" subset.

To better evaluate the networks in light of this overfitting and the skewed results in favour of the dominant class, we utilized precision and recall scores from scikit-learn [12]. These values are defined as in (7) and (8) respectively.

$$\text{Precision} = \frac{\text{true positives}}{\text{true positives + false positives}} \tag{7}$$

$$\text{Recall} = \frac{\text{true positives}}{\text{true positives + false negatives}} \tag{8}$$

Using these metrics along with the accuracy score as evaluation methods, we ran the neural network on each of the three subsets of "Dress-Jeans-Shirts". This was done using the Adadelta optimizer and the manual weighting scheme across all 3 datasets. A detailed summary of the results of these runs can be found in Table II. We found that the full subset attained an overall accuracy of 88.2% by classifying most images as shirts and a few as jeans. As a result, it was unable to classify any dresses and got poor precision and recall for jeans. The even split subset classified almost all images as dresses and none as shirts, resulting in poor precision results for dresses and jeans, in addition to poor recall for jeans. The third subset, the manually cleaned subset, was the only one to classify some images for all classes, but had fairly poor precision and recall overall.

While the results for the cleaned subset are the most promising due to covering all 3 categories, we realized that the results may be due to humans being present in many of the dress images resulting in the network training on humans rather than dresses. For this reason, we chose to evaluate the results of the different optimizers and weighting schemes on the entire "Dress-Jeans-Shirts" subset as it was the second most promising. We then ran all weighting systems detailed in Table I using both Adam and Adadelta optimizers. The summary of these runs can be found in Table III. For this performance comparison, we found that only the manual weight setting along with the Adadelta optimizer, which is the configuration used in all previous tests, was able to obtain results that did not classify all images as shirts. Further investigation and testing is required to understand what is causing these results.

D. Folding Algorithm Results

Using the algorithm for finding folding lines on images of clothing from the Fashion Product Images Dataset [3] proved quite successful. We chose to demonstrate the algorithm on t-shirts as explained above, and were able to attain several results that are comparable to where a human would fold the clothing. These results can be seen in Figures 2 and 3. As can be seen in these images, the algorithm was able to find an accurate centroid and trace lines through the centroid for the "quarters" method. It was also able to achieve good results for "sides-in" technique with a line through the centroid and two more lines, each approximately a quarter of the shirt width away from the sides. This latter method did not prove as reliable as the "quarters" method but still achieved good results and should prove as reliable with further refinement. While these results are mostly presented for the t-shirt class of clothing, the success of the algorithm on this class indicates

TABLE I: Neural Network Weighting Schemes

Weighting System Name	Formula	Weights		
		Dress	***Jeans***	***Shirts***
Manual	N/A	5	5	1
Naive	$w_i = 1$	1	1	1
Inversely Proportional	$w_i = \frac{\max(x_1,x_2,x_3)}{x_i}$	3.51	2.70	1.00
Logarithmic	$w_i = 2\log\left(\frac{\max(x_1,x_2,x_3)}{x_i}\right)$	1.69	1.47	0.60
Polynomial	$w_i = 2\left(\frac{\max(x_1,x_2,x_3)}{x_i}\right)^{1.5}$	13.15	8.89	2.00

TABLE II: Neural Network Testing Subsets Results

Subset	Accuracy Score	Precision, Recall		
		Dress	***Jeans***	***Shirts***
D-J-S	88.2%	0,0	0.20,0.26	0.73,0.77
D-J-S Even Split	6.5%	0.01,0.92	0.03,0.04	0,0
D-J-S Cleaned	49.2%	0.15,0.32	0.26,0.55	0.60,0.13

TABLE III: Neural Network Weight and Optimizer Results

Parameters	Accuracy Score	Precision, Recall		
		Dress	***Jeans***	***Shirts***
Adam - Manual	73%	0,0	0,0	0.73,1.0
Adam - Naive	73%	0,0	0,0	0.73,1.0
Adam - Inv. Prop.	73%	0,0	0,0	0.73,1.0
Adam - Log.	73%	0,0	0,0	0.73,1.0
Adam - Poly.	73%	0,0	0,0	0.73,1.0
Adadelta - Manual	88%	0,0	0.20,0.26	0.73,0.77
Adadelta - Naive	73%	0,0	0,0	0.73,1.0
Adadelta - Inv. Prop.	73%	0,0	0,0	0.73,1.0
Adadelta - Log.	73%	0,0	0,0	0.73,1.0
Adadelta - Poly.	73%	0,0	0,0	0.73,1.0

it would also be able to attain good results on other classes of clothing as defined in the algorithm description. Due to the robust nature of this algorithm, it should apply itself well to other classes of clothing as seen on the sweater and jeans within Fig. 2, while the “sides-in” technique does not apply itself as well to other articles due to the overall nature of the technique.

E. Discussion

Our results for the neural network portion of this project show there is promise for using this network or another similar network such as FashionNet [2] for the task of clothing classification. Overall, this project suffered greatly from the poor quality of the dataset due to the uneven distribution of images, incorrect labels and inconsistent image styles. It is our belief that with a higher quality dataset either found through increased effort or created by hand, the neural network presented would be able to accomplish the proposed task of clothing classification. The results attained for the “Dress-Jeans-Shirts” cleaned subset demonstrates that the algorithm is able to attain reasonably good results with a cleaner dataset, further verifying that a large clean dataset would be able to utilize this neural network. Further work in this area for imbalanced datasets could also include testing more weighting schemes in order to find one that performs better than those presented in this paper. As noted previously, the neural network in this paper can also be expanded in order to classify a larger variety of clothing types, which is another potential area of future work.

With respect to the folding algorithm, we were able to obtain good results for our goals. The folding line detection algorithm has been developed under the idea that clothing would be lying on a table or conveyor belt, separated so that a robot can view a single article at a time on a relatively solid background. Further work will need to be done to account for the possible rotation of various pieces, or accidental folding of parts of an article. This algorithm was developed using ideal circumstances for even, consistent placement of clothing on a solid surface. Wrinkles and folds in the attire greatly affected the edge detection of the shirts for the “sides-in” technique, and so this will need to be researched some more for better results. Additionally, the algorithm as presented in this paper does not make use of generated classes from the neural network, but can be easily integrated with it once the neural network is significantly accurate. While the two methods chosen for folding in this paper are designed for use with t-shirts, the underlying algorithm applies to a large variety of clothing classes, with some good initial results presented for the “quarters” method on a sweater and jeans. To this extent, the method presented can easily be expanded to incorporate other folding methods for t-shirts or for other classes of clothing, which is one area of future work for this algorithm. Before this algorithm is implemented in a real world scenario, more testing would need to be performed in order to ensure the algorithm works on a wide array of clothing. Once the algorithm is sufficiently tested for different scenarios, work will need to be done in order to convert the folding lines generated into motion paths for a physical folding device, such as a robotic arm.

A possible application of the folding algorithm can also be in training a neural network, which may result in higher accu-

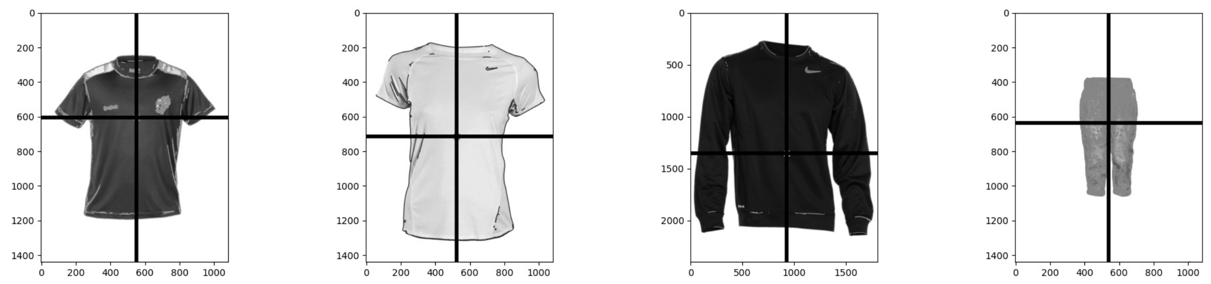

Fig. 2: Examples of “quarters” folding method on multiple articles of various classes

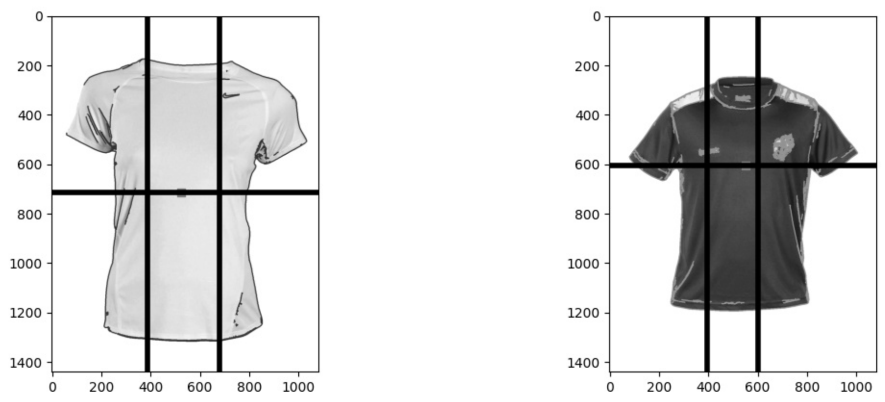

Fig. 3: Examples of “sides-in” method on t-shirts

racy than the traditional approach suggested in this paper. As the algorithm generates the folding lines for the input images, the output can be used in order to automatically generate a training set for a neural network. This neural network could also be used in combination with the classification neural network suggested in this paper in order to develop a unified network for both classifying and determining folding lines for images of clothing.

V. Conclusion

This reports presents two aspects of the process needed for developing an automated laundromat. We first present a convolutional neural network architecture for classifying images of clothing into classes defining how it should be folded, such as t-shirts and jeans. We then describe a traditional edge detection approach for determining fold lines for t-shirts that can easily be extended to other apparel. The neural network is trained and tested with subsets of images from the Fashion Product Images (Small) [1] dataset, and its performance is evaluated for accuracy, precision, and recall to determine the optimal network architecture. The folding algorithm is implemented on several images of t-shirts from the Fashion Product Images Dataset [3] and then visually inspected in order to determine the accuracy of the resulting folding lines compared to what a human would select. We conclude that the neural network architecture is promising but requires further refinement and investigation, along with more testing needed with different datasets. We further conclude that the traditional folding algorithm approach using edge detection is successful but requires more testing and refinement for real world implementation, and that it may be useful for generating training data for a more accurate neural network to be used instead.

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Work Divide

Both group members worked evenly on every aspect of the project. Maryse provided the GPU while Justin provided the tea.

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