Imagify & sustAInability Report
9 July 2023

The textile industry is one of the leading contributors to carbon emissions. This has significant consequences in terms of resource extraction, pollution and environmental sustainability. Only from 2000 to 2015, the total amount of clothing produced doubled. Whereas, extending the life of a garment by nine months brings 20 to 30 percent reduction in carbon, water and waste footprint; in addition to 20 percent reduction in supply, wash and disposition costs (ECOS, 2021). Initiatives in the textile industry are essential to achieve the goals set by the Paris Agreement. Stakeholders from business, government and transnational spheres are becoming vital players to respond to climate action in the fashion industry. Consumers are also becoming more aware of the environmental footprint of product waste, and are thereby signaling willingness to gravitate towards solutions that improve product durability and recovery. Hence, both the sectoral and environmental gains are way too important to give up.

The product development procedures need smarter inputs and standards to offer better general durability for the end customer, endure less costs for product development, and limit the use of hazardous chemicals and microplastics. Furthermore, EU initiatives that target waste, pollution and carbon footprint will come to the forefront as these initiatives will be followed by regulations and procedures at governmental stages. ECOS (2021) suggests all stakeholders of the textile industry collaborate on coming up with minimum durability requirements for garments, allowing consumers to have an idea of life expectancy for a product. The innovations at the product development stage providing more intelligent product development suggestions that take into account the cost, supply, design, and environment aspects will become crucial.

Imagify provides businesses the perspective on product improvement with the goal of increasing overall garment lifespan. Consumers prioritize product quality in purchase decisions. Imagify creates value mainly by providing a more direct feedback loop between the consumer and the brand, diagnosis and analysis of product weak spots, and building relationships with the customers that are built on transparency on product durability. Imagify seeks to enhance the mainstream understanding on product damage and envisions a dynamic, farsighted player that instantly translates consumer feedback to the product development process instead. Through a combined analysis of product reviews and product images provided by customers that display wear and tear, defect, improvement suggestions, and loved features; brands become enabled to access suggestions and analyses that are directly translatable to product development.

To truly understand the challenge, we started off conducting research on what durability means, how it fits into the fashion industry's discourse on sustainability. We identified four different components of customer reviews, namely

I. fatal defects
II. normal wear and tear
III. loved features and
IV. suggestions for improvement

We realized that reviews are usually not collected at the right point in time to get useful feedback to optimize product durability. By asking customers to rate the product after a couple of days or weeks of purchase, brands are not able to find out how their products perform over their entire lifecycle. Reason for this is that they fail to capture insights on normal wear and tear. As reviews often contain several of the components (such as "I love the color but unfortunately it started to fade after five months"), we realized that this differentiation was an aspect Imagify should capitalize on. To find out how to best go about this, we paid a closer look at who its users will be and at what they truly need.

We wanted to ensure that Imagify is not only one of many digital tools. Instead, we want the platform to become an encompassing digital enabler helping in all development stages to increase their products' lifecycle. To ensure this being the case, we decided on a user centric approach to the challenge. We conducted an unser analysis to understand who the different problem owners within the brands are, what their goals are, what they are struggling with, which digital help they would like to receive and how this could translate into specific Imagify algorithms, functionalities and dashboards.

The user groups we identified were engineers, designers, product development, supply chain and operations, marketing and sales, quality control and testing, sustainability officers, customer support, data analysts and the brands' top management. It was really impressive to see how many people could benefit from an AI customer review and quality control tool and to see that this way all these users could get enabled to create more durable and sustainable fashion items.

In identifying the different user groups, we realized that the data they are particularly interested in varies. While the top management would like to know what is going on in general and like to be able to get a quick overview, designers are trying to develop aesthetically pleasing products that perform well, meet customer needs and align with the brand's vision. To do so, they need access to reviews mentioning the user's most loved features (like the feel of a specific material used) and wishes for improvements (for instance adding an additional zipper). Normal wear and tear would be information they are not particularly interested in - there's quality control and testing to overcome these challenges. Engineers are most interested in hearing about the fatal defects and wear and tear that occurred in order to optimize the items' performance, functionality and durability. What all these different user groups have in common is that they are lacking access to processed data that is filterable for the information the specific users need the most. As manual labeling of reviews works on a small scale but is not scalable, we continued to develop an AI Action Plan to solve this issue.

Our short-term solution consists of two parts, namely a customer review analyser and a chatbot. As part of our AI Action Plan, this first solution is meant to provide IMAGIFY with tools to launch in the shortest time possible that also deliver high value for the users of the platform. This solution is also a necessary base that would serve the development of the platform and the addition of further features.

The review analyser AI tool would be used to evaluate the degree to which IMAGIFY's reviews correspond to the four categories (fatal defects, normal wear and tear, improvement suggestions and loved features). This tool is a crucial first step that will provide IMAGIFY with a product for its users that reveals key insights along the four categories. This tool would be developed based on a large sample of reviews. The sample would include 50 % ChatGPT-generated reviews that fall perfectly under just one of the four categories and 50 % manually-labeled Amazon reviews of real customers. Real user reviews mostly fall into more than one of the categories, hence they would be labeled using floating point values for each category that add up to 1. This approach of combining ChatGPT and real review data aims to achieve finer granularity and flexibility of the model. Our group has created a dataset of 100 labeled reviews which is supposed to illustrate the data collection approach and to serve as the first step toward building a dataset to train the customer review analyser. After the data is collected, it would be preprocessed and as part of this step tokenized and cleaned from stopwords. Then the data would be split into training, test and validation sets and a recurrent neural network method would be used to train the initial model. Afterwards, the model would then be evaluated for its accuracy, precision and recall. Depending on how the model scores on these evaluation metrics, adjustments might be made to the data collection approach and the preprocessing steps. Once the model demonstrates sufficient results it will be deployed on IMAGIFY's review data to extract categories.

The chatbot would compliment the analyser by offering more detailed insights on the reviews such as what products have been worn the longest or which are the most common areas of defects. The chatbot would be built using GPT3 and the LLamaIndex framework to extract information from IMAGIFY documentation including reviews and other relevant files.
The combination of these two tools as a first solution would be especially useful for small businesses that aim to improve their products and have fewer resources. In the short term, the platform is most useful to users in less specialized roles and requires good understanding of the reviewed products and of the IMAGIFY tool to be able to maximize the value extracted when prompting the chatbot.

The mid-term solution builds up on the review analyzer with the introduction of the visual dimension to the model. It consists of two pieces: an image analyzer, and a dynamic heatmap. The language-based learning introduced at the short-term schedule provides insightful perspectives to product development processes, yet, when the review-based learning is bridged with a dynamic image analyzer, the scope of the solutions multiply.

The image analyzer processes images provided by end customers across various product feedback categories. These would include images of defective products, products that endured normal wear and tear after a relatively long and intensive use of the product, improvement suggestions, and loved features. The image analyzer is built with a visual deep learning algorithm that is rendered to distinguish between these categories through an automatic differentiation module that, through the introduction of visual data, becomes enabled to understand the key characteristics of different feedback categories across different zones of the garment. This model would be trained to process different dimensions of visual data (pixel patterns, color, tensors, etc.). The neural network of the training would parallelly process original product image across the lines of different feedback categories, additionally logging the specific location the feedback refers to as a coordinate input, filtered as intervals. Then the model would be tested with the introduction of an alternative dataset that would not be used in the training of the model, to evaluate the accuracy of the feedback location and precision of the feedback category. The model would be optimized with a series of learning phases and modifications following these phases.

The following stage of the mid-term solution would be to compose a dynamic heatmap that is able to highlight generic product feedback categories with visual emphasis on the cruciality of the feedback, the specific location that the feedback refers to, and the frequency of the certain feedback category. The heatmap is a more advanced and complex analysis tool compared to the visual analyzer, as at this stage the text-based deep learning scheme at the review analyzer and its visual processor counterpart come together to form a comprehensive model that allows the visual and textual learning to feed off one another. The neural network between the textual and visual data is constituted by the juxtaposition of location emphases provided in the reviews and the location learning that the visual analyzer provides. A complex cross-dimensional deep learning architecture has to be developed that is conclusively able to provide compact outcomes and analysis for the user to access the most essential product feedbacks easily. Currently, a more detailed description of the architecture of this complex model would be redundant, as the learning outcomes and the fundamental mechanisms of the review analyzer and the visual analyzer will be dependent on the learning schemes of both models that were introduced and described before.

As both the visual analyzer and the heatmap are successfully put into the action, the users will be able to reach the analyses of product reviews and visual feedback conveniently. Herein, differing user needs and priorities would be matched up with different parts of the analyses. For instance, a product developer with a focus on material durability could filter the analysis essentially containing feedback and visuals on defects, wear and tear while a designer being able to filter improvement suggestions. Through this, the significant gap between the customers and product developers would be minimized, opening up the opportunity for durable and consumer-friendly products that limit environmental pressure of the textile industry.

The long-term solution for Imagify would include leveraging AI tools in ways that would take longer to implement effectively. These AI uses would include, but are not limited to, extracting location data to build an effective product heat map, and AI suggestions regarding what changes could be made to improve the lifespan and quality of a clothing item.

With more time that can be used for development, there is also a large amount of time available for usability testing. In order to deliver a polished and immediately deployable product, research should be conducted to discover what parts of a user interface are user-friendly or confusing for those using the site. However, until this user testing is completed, it is difficult to predict what a final deliverable may look like.

For the sake of showing what the future of Imagify could look like with the help of AI tools, we developed a sample deliverable despite these challenges. Figure 1 illustrates our ideas of a simple heatmap showing which areas for issues and suggestions were most common. We also added an option to filter between the different types of data collected: fatal defects, normal wear and tear, improvements, and loved features. This feature allows engineers and designers to zoom in on specific fixes instead of mixing in all of what customers love with fatal defects that absolutely must be addressed.

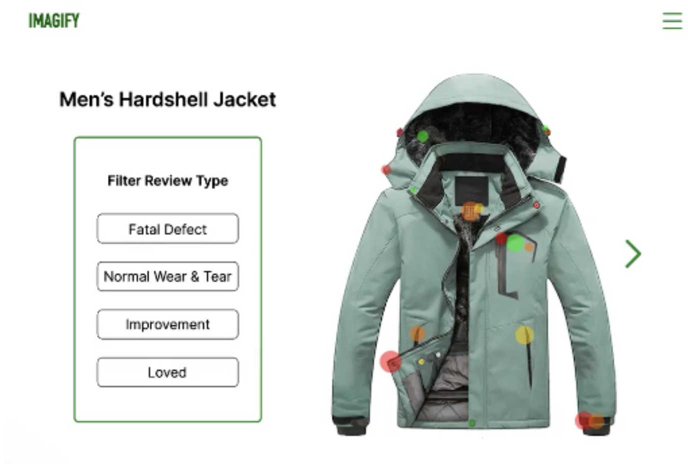

Figure 1: A final UI sample development

Scalability of the product was a large concern before our group started working to develop AI solutions. In its current state, it is very difficult to use Imagify to determine which problems or product areas are most common/pressing. Our heat map addition improves the scalability slightly by showing more specific areas and issues, but in an extremely large scale project, it will not be able to keep up with all of the reviews either. With more time for development, however, these concerns can be overcome. In general, with the help of AI tools, the outlook for Imagify and fashion sustainability is very positive.

Being a group consisting predominantly of social science students, at first we were struggling with some insecurities on if we were expected to to develop AI ourselves and what our contribution could be. Luckily, Stefan managed to take those insecurities away from us by explaining that although he was looking for immediately usable outcomes, they do not have to come in the form of code and that it was totally valid to just get going and see where we end up being able to contribute. We agreed on a daily meeting in the morning to report our progress and get feedback and new insights. Stefan's enthusiasm for design thinking and project management methods using different tools for visualization really helped us to organize our first ideas.

We started off conducting research on the one hand on the categorization of defects on fashion items and at the same time on available AI models that could be of use. It quickly became clear that Maria and Berk were interested in the more technical parts of the challenge and that Sarah had very valuable UI design skills. Verena and Zeynep were focusing on the project management related part of the challenge and from an already comparatively early point onwards on developing storytelling ideas for the final pitch. This division of tasks appeared naturally and it proved to be very valuable to update each other regularly on what we were working on in order to enable us to jump in and help out wherever there was a need.

Overall, the sustAInability project and being able to work on the real world issues of an early stage AI startup striving to enable sustainability was a great experience. It felt great seeing how we could apply the knowledge we acquired in the input sessions to a real world challenge and to broaden our knowledge about the role of durability in the sustainability debate and how AI can be used to make a change. Besides this, the great mentorship we received throughout the week was very helpful for each one of us to develop personally and as a team and the agile project management skills we acquired will certainly prove to be successful in the future. We are very proud of what we achieved during the sustAInability project week and want to thank Charlotte Böhm, Helene von Schwichow and Stefan Hauser for making this possible, the great mentorship, the trust we were given and for opening up the sustAInable startup world to us.

References

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