CHECK IN:
ESTIMATING ROOM MENTAL HEALTH SUITABILITY USING COMPUTER VISION

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Abstract. The interplay between physical environments, particularly indoor spaces, and psychological well-being is an emergent research area with significant practical implications. Despite acknowledging the positive effects of clean and luminous spaces, robust methodologies to evaluate such environments objectively are scarce. This study addresses the challenge by proposing to estimate an environment's influence on well-being from a single photograph. Utilizing a Convolutional Neural Network—selected for its prowess in pattern recognition—is chosen to analyze specific features like messiness and brightness, which have been empirically linked to comfort and mood. This analysis is part of a broader set of variables our comprehensive model assesses, aiming to provide a nuanced environmental quality assessment tool. The aim is to quantify this analysis into a suitability score that reflects an indoor space's potential to enhance well-being, based on the model's confidence. Our model is trained on a diverse and ethically sourced dataset, including anonymized student contributions and internet images, preparing it to offer refined classifications. The ultimate objective is to inform non-clinical, preliminary evaluations of environmental quality and suggest enhancements for spaces used in daily life.

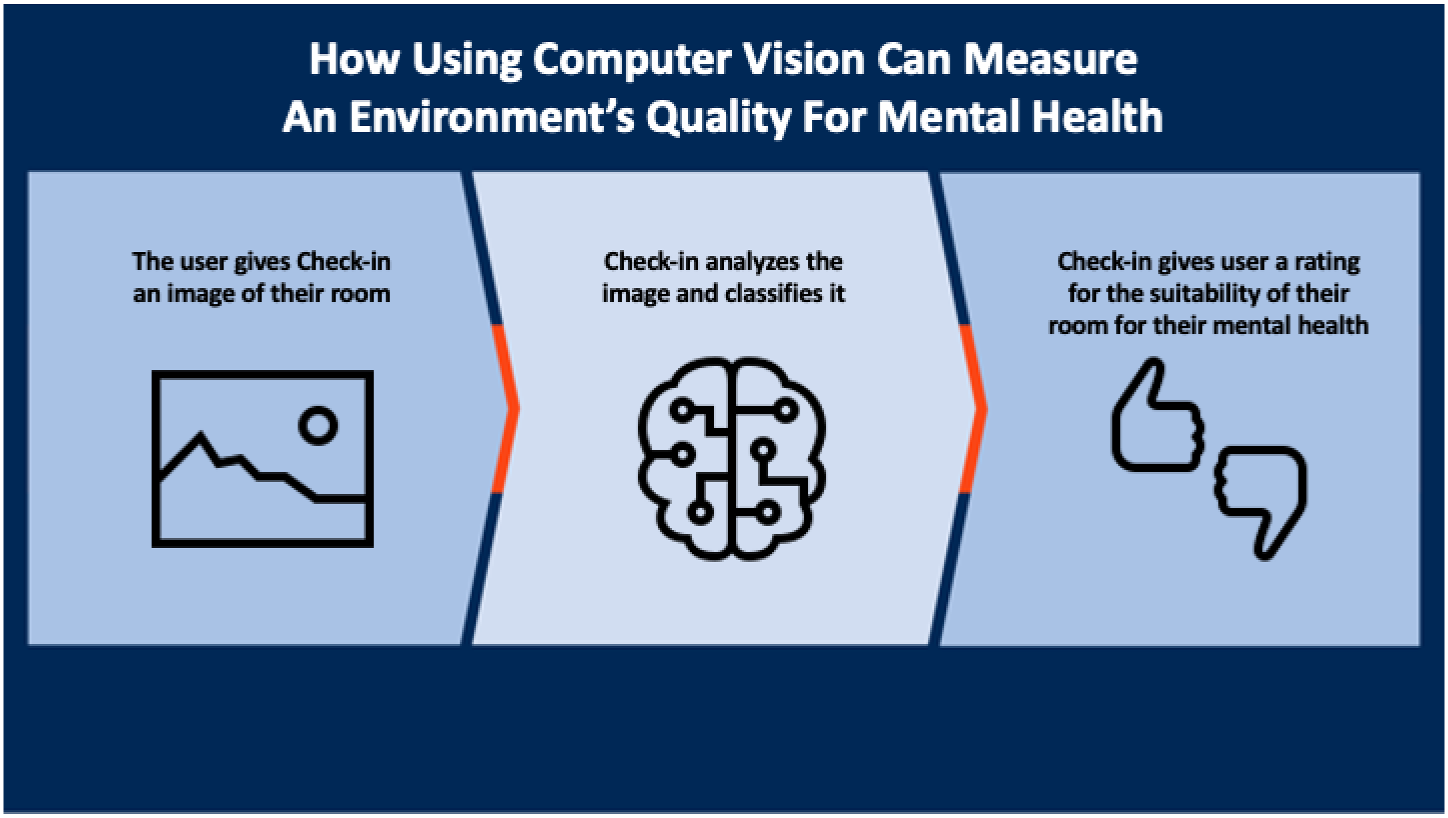

Figure 1: The image illustrates the user journey with Check-in, utilizing computer vision technology. Initially, the user uploads an image of their living space. Subsequently, Check-in processes the image through its sophisticated algorithm, assessing factors that potentially influence mental well-being. Finally, the user receives a suitability rating for their environment, aiding them in making informed decisions about their surroundings in the context of mental health.

1. Short Statement of Work

1.1. Scope

Our research tackles a crucial yet under-explored area - understanding how the physical indoor environments we inhabit impact our psychological well-being. While this connection carries immense practical significance, the lack of robust, objective evaluation methods has hindered progress. That's where our innovative approach steps in. We've developed a machine learning model leveraging the ResNet50 architecture that can assess an indoor space's potential influence on mental health from just a single photograph. By analyzing empirical visual cues linked to mood and comfort like cleanliness and lighting, it quantifies these attributes into a "suitability score" reflecting how conducive that environment may be for enhancing well-being. This not only elucidates the complex interplay between surroundings and mental health but provides a practical tool for preliminary, non-clinical evaluation of environmental quality - paving the way to optimize the spaces that shape our daily experiences for psychological nurturance based on evidence.

1.2. Technical Objectives

This project has two primary objectives that converge cutting-edge data techniques with psychological principles. First, we aim to establish a robust data preprocessing and augmentation framework to ensure input data consistency and diversity, optimizing the training of our deep learning model - a ResNet50 architecture pre-trained on ImageNet. This enhances the model's ability to generalize from training data to real-world applications like classifying indoor spaces based on cleanliness and brightness levels. Secondly, by developing this machine learning model to generate quantitative "suitability scores" for indoor environments, we seek to provide actionable insights into how the physical characteristics of these spaces can be optimized to promote psychological health, comfort, and well-being. Through these objectives, we offer a novel interdisciplinary approach bridging environmental psychology and computer vision, with the potential to reshape how we design and experience the indoor spaces that significantly impact our daily lives and mental health.

1.3. Technical Approach

Our technical approach leverages the power of machine learning, specifically the ResNet50 architecture renowned for image recognition and pre-trained on ImageNet for rich foundational knowledge. We implement a comprehensive data pipeline including resizing, normalization, standardization, and an innovative augmentation strategy incorporating techniques like flipping, rotation, cropping, zooming, brightness/color adjustments to artificially expand dataset diversity and simulate real-world conditions. This meticulous preparation enhances model generalizability and robustness for accurately classifying indoor spaces based on cleanliness and brightness through a refined prediction strategy consistent with training/validation processing. Underpinning our objective to develop a nuanced tool estimating indoor environments' psychological impact, this approach combines advanced computer vision techniques like augmented ResNet50 with environmental psychology principles, offering a scalable solution for quantifying environmental quality factors impacting mental well-being.

2. Problem Statement

The connection between the physical environments we inhabit and our psychological well-being has gained increasing relevance, especially with urbanization trends driving us to spend more time indoors. A major area of focus is the quality of indoor spaces where we spend a considerable portion of our lives - homes, offices, schools and the like. Research reveals that environmental factors like cleanliness, lighting, and organization profoundly influence mental health, productivity, and overall life satisfaction. For instance, a study by Evans, Wells, and Moch[1] found that poor housing quality and high clutter levels are associated with greater psychological distress among residents. With estimates suggesting we spend up to 90% of our time indoors[2], the impact of environmental quality carries immense weight, affecting millions globally.

However, despite this well-established influence of indoor environments on well-being, there exists a noticeable gap in our ability to objectively assess and quantify this impact. Most existing assessment methods rely on subjective reports or are limited to clinical settings[3], failing to account for the daily indoor spaces where people spend the majority of their waking hours. Our project directly addresses this need by developing an accessible machine learning tool to evaluate indoor environments through visual cues. Specifically, it quantifies key factors like cleanliness and brightness that have been empirically linked to comfort and mood. This scalable, tangible metric of environmental quality enables individuals and organizations to assess and enhance their living and working spaces for improved mental health. By providing an objective, widespread solution to fill this critical gap, our work offers the potential to directly benefit the well-being of millions by optimizing the indoor environments that shape our daily experiences.

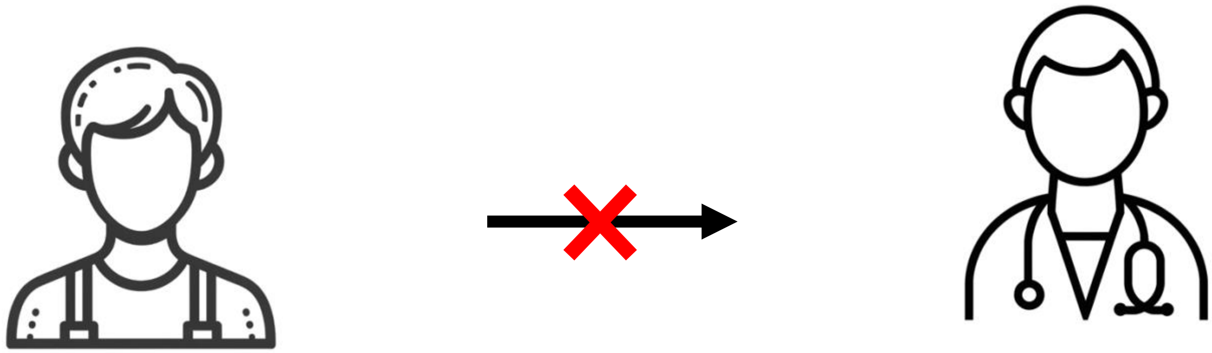

Figure 2. The barrier to mental health support is symbolized here, highlighting the disconnect between individuals and access to mental health professionals[4]. This represents a key challenge that Check-In seeks to address by providing an accessible environmental assessment tool for those who might be unaware of the influence their surroundings have on their mental health or who are unable to seek professional advice.

3. Technical Background

3.1. State of the Art

Assessing and classifying room cleanliness objectively through computational methods sits at the intersection of computer vision, image processing, and machine learning. Recent advancements in these fields have unlocked innovative ways to analyze indoor spaces - something with wide-ranging applications from residential well-being to hospitality management.

A pioneering study by Ferrari, Roster, Crum, and Pardo dove into the psychological dimensions of clutter, revealing that a staggering 20-25% of people exhibit chronic procrastination impacting their ability to maintain organized living spaces. This clutter doesn't just affect social relationships - it contributes to negative emotions and diminished psychological well-being[5].

In the computer vision realm, Suparni, Rachmi, and Al Kaafi utilized support vector machines (SVM) and neural networks (NN) to classify room cleanliness from digital images. Using a dataset of 199 images, their NN model achieved an impressive 98% classification accuracy, outperforming SVM and highlighting deep learning's potential in this context[6].

These studies exemplify the strides made in applying machine learning to assess environmental conditions like cleanliness. However, they also display challenges like image quality, varying lighting, and cleanliness being somewhat subjective. While highly accurate, neural networks' success emphasizes the need for extensive training datasets, which can be scarce or difficult to obtain in some scenarios[7].

Moreover, integrating these computational methods into user-friendly, practical tools for non-experts remains an area needing further work. Current systems demonstrate feasibility but often lack intuitive interfaces necessary for widespread adoption outside research or specialized domains.

In essence, while significant progress has been made in using computational techniques to evaluate room cleanliness and clutter, ongoing research is needed to refine these methods, enhance accessibility, and ensure effective real-world application across diverse environments.

3.2. Solution

At the core of our solution for objectively evaluating room cleanliness and its psychological impact lies a machine learning framework powered by the ResNet50 architecture. This deep residual learning model excels at extracting intricate features from visual data, thanks to its pretraining on the massive ImageNet dataset[8]. Our approach goes beyond simple image processing by leveraging ResNet50's capabilities to integrate a multi-dimensional analysis of environmental quality factors like spatial arrangement and ambient lighting. This allows our system to paint a more comprehensive picture of cleanliness.

To build a robust training dataset, we've collected a wide array of real-world indoor settings, enabling our model to discern and classify cleanliness across a nuanced spectrum - a step up from previous binary clean/messy classifications. This rich dataset enhances accuracy and addresses the limitations of prior methods. What will really set our solution apart, however, is its planned ability to translate those cleanliness assessments into practical recommendations for improving spaces. Thanks to an innovative interpretive layer, we map the visual patterns detected by the model to their potential psychological implications on comfort and interpersonal dynamics.

Designed for accessibility, our user-friendly interface streamlines the assessment process for anyone from individual homeowners to professional facility managers. By innovatively combining cutting-edge ResNet50 technology pretrained on ImageNet with environmental psychology principles, we offer a fresh perspective on quantifying cleanliness and its impact. Our aim is to empower people to foster living and working spaces that enhance well-being and productivity through optimized cleanliness and spatial arrangement.

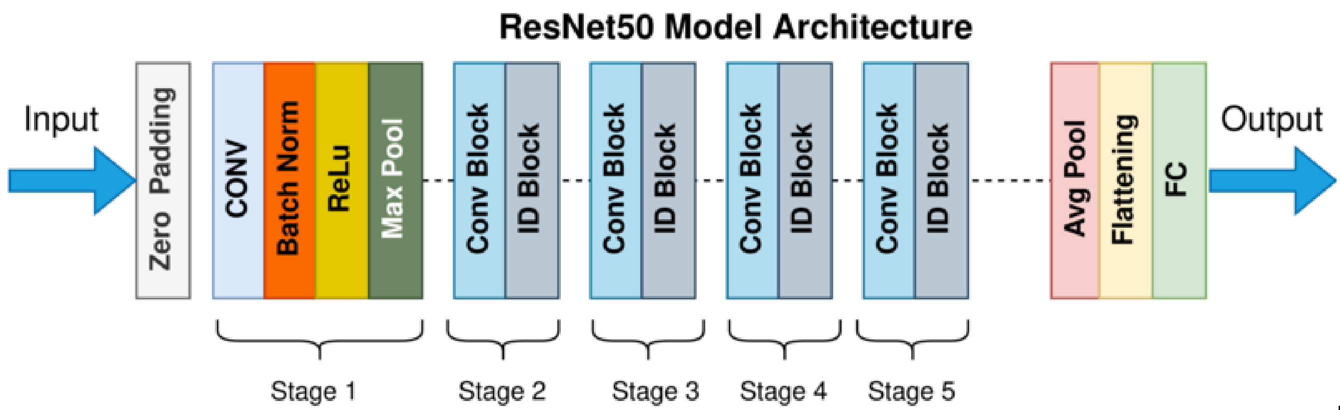

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Figure 3. This diagram presents the architecture of a ResNet50 deep learning model. The input image first undergoes zero padding before passing through a convolutional layer (CONV), followed by batch normalization (Batch Norm) and a Rectified Linear Unit (ReLU) activation function. It then proceeds through a max pooling layer (Max Pool) before entering a series of convolutional blocks (Conv Block) and identity blocks (ID Block) across five distinct stages. Each stage consists of several convolutional and identity blocks that help the model learn hierarchical feature representations. Following the final stage, the architecture concludes with an average pooling layer (Avg Pool), a flattening step to convert the multidimensional data into a 1D vector, and finally, a fully connected layer (FC) that outputs the classification results. This architecture enables the model to effectively learn from complex visual data, making it suitable for a wide range of image recognition tasks.

4. Technical Objectives

Our project aims to push the boundaries where computer vision meets psychological well-being by developing a cutting-edge model to assess room cleanliness and its far-reaching mental health implications. Here's how we plan to advance our work:

1. **Expand and Diversify Data Collection**: To enhance accuracy and real-world applicability, we'll broaden our dataset to encompass a wider range of indoor environments. This involves collaborating with organizations across sectors to capture diverse room conditions and cleanliness levels that our model can learn from.

2. **Advanced Model Development**: Building on the initial success of ResNet50, we'll explore integrating additional deep learning architectures and multi-modal data processing capabilities. This allows us to consider other influential environmental factors like ambient noise and air quality that impact psychological well-being.
3. **User-Centric UI Design and Prototyping**: A major focus will be developing an intuitive, user-friendly interface that streamlines the process of uploading images for analysis while providing clear, actionable feedback. Potential end-users will be involved to ensure the UI meets their needs seamlessly.
4. **Rigorous Validation and Iterative Refinement**: Our enhanced model will undergo comprehensive technical validation and real-world user testing to ensure its effectiveness and usability. User feedback will drive an iterative refinement process, with a keen eye on aligning the model's recommendations with the latest psychological research on environmental factors and well-being.
5. **Pilot Deployment and Evaluation**: With a robust solution in hand, we'll conduct a pilot deployment in a controlled environment to evaluate its real-world impact on room cleanliness and, crucially, the well-being of users. This will provide invaluable insights to identify remaining gaps and further enhance our solution.

Technical Objectives:

- Objective 1: Achieve an accuracy rate of over 97% in classifying room cleanliness through the enhanced model, surpassing current benchmarks.
- Objective 2: Develop a scalable, user-friendly platform that can process images and provide feedback in real-time, accessible to non-technical users.
- Objective 3: Validate the model's effectiveness in improving psychological well-being through a pilot study, aiming for a measurable improvement in user-reported mental health indicators.

Hypotheses and Assumptions:

- We hypothesize that a more comprehensive analysis of room environments, beyond cleanliness, will have a significant positive impact on psychological well-being.
- We assume that users prefer straightforward, actionable advice on improving their living spaces, which can be provided through an advanced, yet accessible technological solution.

Next Detailed Steps:

1. Data Collection Expansion: Engage with partners and conduct targeted data gathering sessions to enhance the diversity of our dataset.
2. Model Development and Integration: Begin integrating additional environmental factors into our model, exploring the use of supplementary neural network architectures.
3. UI Prototyping: Start the design process for the UI, focusing on simplicity and user engagement.
4. Validation Framework Establishment: Set up a framework for both technical validation and user testing, including metrics for success and user feedback mechanisms.
5. Pilot Study Preparation: Plan and prepare for a pilot deployment, identifying participants and setting objectives for assessing the impact on well-being.

Resolution to Stated Problem:

This strategic approach directly addresses the need for an advanced, accessible tool that not only assesses room cleanliness but also considers the broader environmental factors impacting psychological well-being. By developing a model that provides actionable insights based on a comprehensive understanding of indoor environments, we offer a unique solution that bridges the gap between technology and mental health improvement.

Solution Impact:

By fulfilling these objectives and following through on the outlined steps, we aim to create a practical, scientifically backed tool that addresses the unmet need for objective assessment of room mental health suitability.

This solution not only innovates in the technical field by combining computer vision with environmental psychology but also provides tangible benefits by empowering individuals and organizations to make data-driven improvements to their living and working spaces, thereby enhancing mental health and well-being.

5. Technical Challenges

In charting the course for our project, which applies ResNet50 architecture to evaluate the influence of room cleanliness on well-being, we anticipate a series of technical challenges that could impact our journey to successful completion.

A significant hurdle lies in assembling a dataset reflective of the vast array of indoor environments. The risk here is that the data might not represent the full spectrum of real-life conditions, such as varying lighting or diverse decor styles, potentially leading to a model that doesn't perform well universally. To tackle this, we're taking extra care in our data preparation, adding a range of real and synthetic images to train a more adaptable model.

Another potential stumbling block is the ResNet50 model itself. Its deep and complex structure is prone to overfitting—basically, it might get too tuned to our training data and not generalize well to new, unseen images. This is particularly tricky given that we're treading the fine line between physical clutter and its psychological effects. Our safeguard here includes robust validation steps, like cross-validation, to ensure our model can reliably interpret new environments.

When it comes to user experience, translating our model's findings into clear, actionable advice presents another challenge. It's essential that our interface is intuitive, providing recommendations without overwhelming users with too much technical detail. We plan to refine this aspect through iterative design and user testing.

If we notice our model's predictions veering off course, we're prepared to step back to the last point where things were on track. Regular check-ins at development milestones will help us identify and address any issues early on. The toughest roadblock will likely be blending the precision of our machine learning model with the subtleties of environmental psychology. We aim for our system to not just identify cleanliness levels but to understand their connection to well-being—a complex task that goes beyond traditional image classification.

In conclusion, while we face formidable tasks ahead, our project is underpinned by a solid plan to navigate these challenges. Through meticulous data handling, vigilant model validation, user-focused design, and a clear strategy for potential setbacks, we are geared up to advance our project towards its envisioned goal.

5.1. Preliminary Work

Describe To date, our team has made considerable progress in laying the groundwork for our project, which seeks to assess the cleanliness of a space and its psychological impact using the ResNet50 machine learning model. The first four of these steps are represented in the flowchart below.

Completed Milestones:

1. **Data Collection**: We've successfully compiled an extensive dataset comprising images of various indoor environments. These images have been sourced from volunteer submissions and online databases, ensuring a rich variety reflective of different living spaces.
2. **Data Preprocessing, Augmentation**: The dataset has been preprocessed, which involved converting the images to a consistent size and color scheme, normalizing the pixel values, and standardizing the images to ensure uniform input to the model.

Figure 4. The data preprocessing flow used in Check-in, starting with loading the image, converting it to RGB color scheme, resizing it, normalizing and standardizing it, and then splitting the dataset.

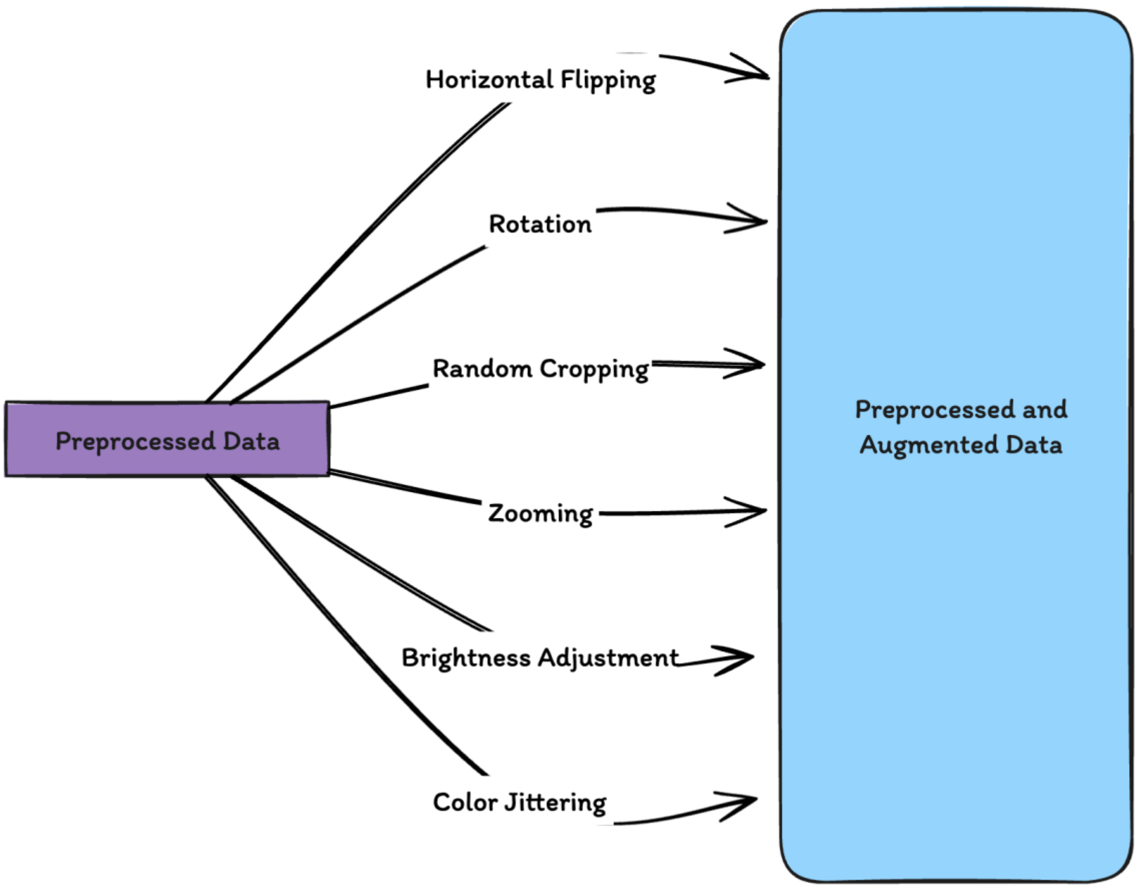

Figure 5. This illustration depicts the augmentation techniques applied to the preprocessed dataset for training the Check-In model. To enhance the robustness and generalizability of the model, the dataset was augmented through horizontal flipping, subtle rotations, random cropping, zooming, brightness adjustments, and color jittering. Such augmentation simulates a variety of lighting and orientation scenarios, enriching the training data and consequently improving the model's ability to generalize from visual input.

3. **Model Selection and Training**: We selected the ResNet50 architecture due to its proven success in image classification tasks[8]. Leveraging its pre-training on ImageNet, we've further trained the model on our dataset to recognize and classify levels of cleanliness and room organization.

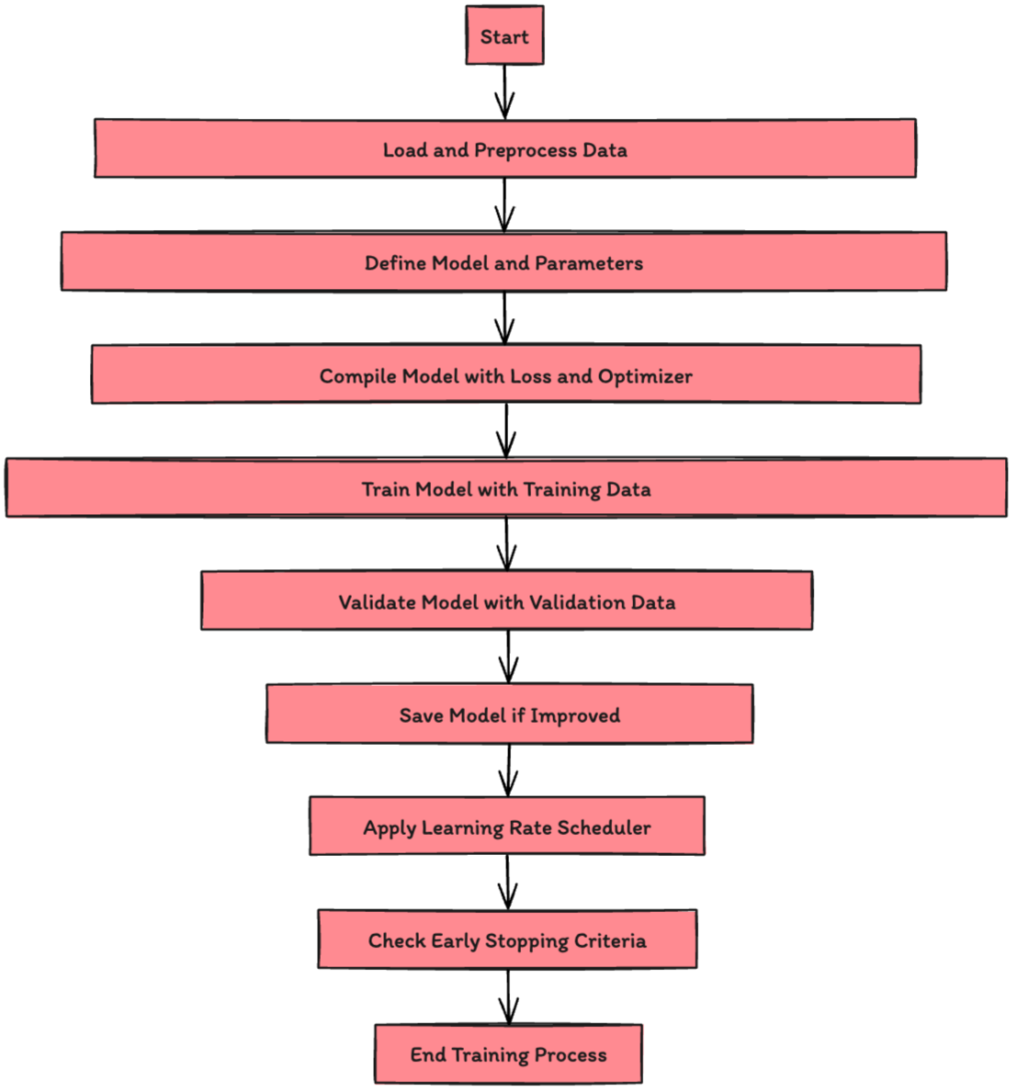

Figure 6. The diagram presents a sequential overview of the training loop for the Check-In model. Starting with data loading and preprocessing, it progresses through model definition, compilation, and training phases. Validation follows each training epoch, with model improvements prompting a save. Learning rate adjustments and early stopping criteria are applied to optimize performance and prevent overfitting, culminating in the conclusion of the training process.

4. **Initial Model Evaluation**: Post-training, we conducted an initial round of model evaluation using a subset of our data. The model has shown promising accuracy in distinguishing between clean and less clean spaces, and we've started fine-tuning it to improve its precision further.
5. **Development of the Interpretive Layer**: A rudimentary version of the interpretive layer has been developed. It begins to link the visual cues identified by the model to potential psychological impacts, setting the stage for the actionable insights we plan to provide in the future.

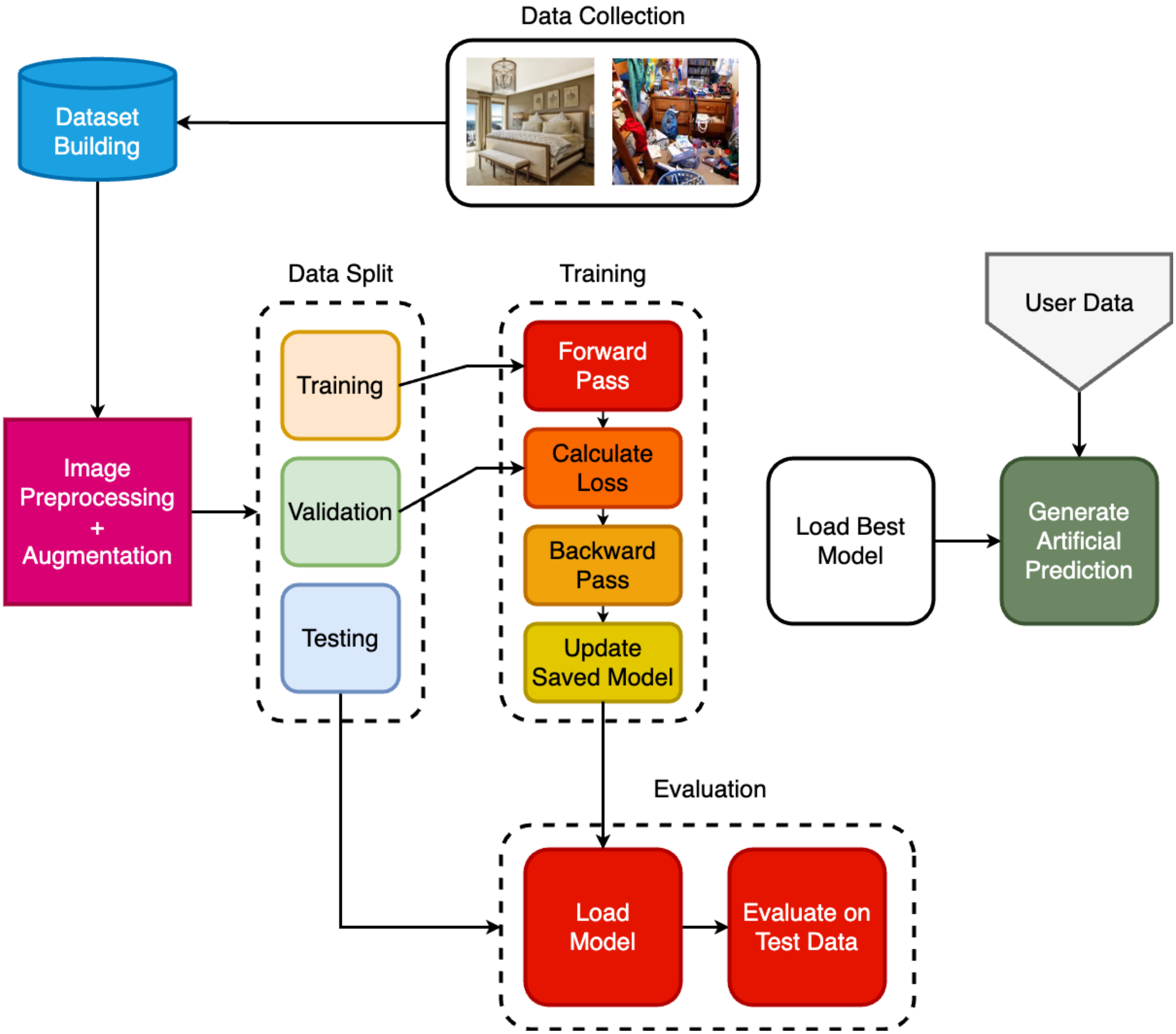

Figure 7. This flowchart outlines the stages in developing a machine learning model for evaluating indoor environmental quality. The process begins with data collection, assembling a diverse dataset of indoor images, showcasing varying levels of cleanliness and organization. This dataset undergoes preprocessing and augmentation to enhance its robustness. It's then split into training, validation, and testing sets. The model undergoes training, involving forward and backward passes to adjust weights based on calculated loss, resulting in a saved model. The best-performing model is then loaded and employed to generate predictions on new user data. Concurrently, the saved model is rigorously evaluated on a separate test dataset to assess its performance. This cycle represents a comprehensive approach to creating a tool that can quantitatively assess and potentially improve indoor spaces, impacting mental health and productivity.

Work Plan for Future Work

Our current focus is on refining and advancing the model to ensure it meets our objectives of accurately assessing room cleanliness and its psychological impacts. Our plan to address the challenges and meet the technical objectives is organized into several key tasks:

Task 1: Model Enhancement

- **Milestone 1:** Integrate more sophisticated data augmentation techniques to better handle the diversity of real-world scenarios, aiming to improve the model's generalizability.
- **Milestone 2:** Apply regularization methods such as dropout and batch normalization to mitigate overfitting.
- **Milestone 3:** Conduct hyperparameter tuning to optimize model performance.
- **Milestone 4:** Achieve a predetermined accuracy threshold on the validation set, confirming that our model enhancements are effective.

Task 2: Data Expansion and Diversification

- **Milestone 1:** Curate additional images, focusing on underrepresented scenarios in the current dataset to increase diversity.
- **Milestone 2:** Annotate new data with greater detail on cleanliness and psychological impact, involving domain experts if necessary.
- **Milestone 3:** Double the size of our dataset while maintaining quality, ensuring robustness in the model's classifications.

Task 3: Development of the Interpretive Layer

- **Milestone 1:** Create a framework for the interpretive layer that can process the model's output into psychological impact insights.
- **Milestone 2:** Work with psychologists to validate the interpretive model's findings and refine the criteria it uses to draw conclusions.
- **Milestone 3:** Develop an initial version of the interpretive layer that aligns with psychological standards and integrates seamlessly with the model's output.

Task 4: User Interface Development and Testing

- **Milestone 1:** Design a user interface prototype that clearly presents model results and recommendations.
- **Milestone 2:** Conduct user testing with a small group to gather feedback and identify areas for improvement.
- **Milestone 3:** Launch a fully functional interface that is user-friendly and informative, catering to the needs of both laypeople and professionals.

Task 5: Validation and Iteration

- **Milestone 1:** Set up a continuous validation system using a new set of images that were not part of the training or initial evaluation.
- **Milestone 2:** Iterate on the model based on validation results, adjusting as needed to improve accuracy and reliability.
- **Milestone 3:** Achieve consistent performance metrics across multiple validation datasets, demonstrating the model's robustness and reliability.

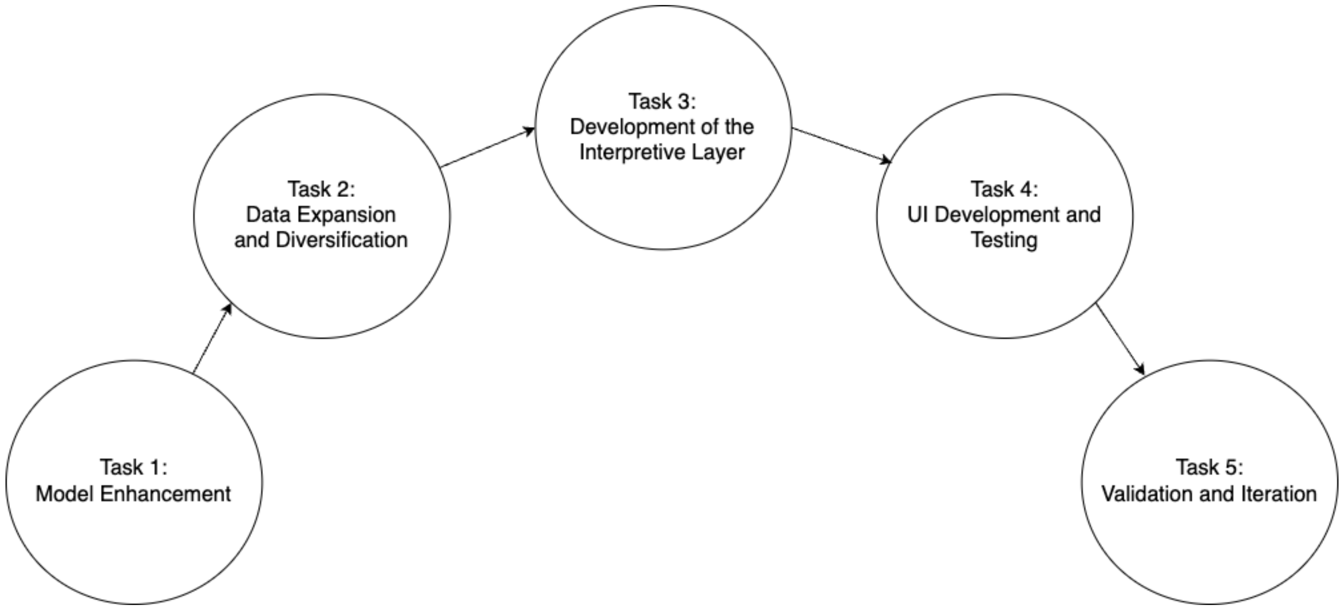

Figure 8. The workflow illustrates the planned progression of tasks for future enhancements of the Check-In project. It begins with Task 1, focusing on Model Enhancement to refine the core algorithmic performance. Task 2 involves Data Expansion and Diversification to ensure the model's robustness across various scenarios. Following this, Task 3 develops an Interpretive Layer to make the model's outputs understandable to users. Task 4 encompasses UI Development and Testing, which involves crafting and refining the user interface. The cycle concludes with Task 5, where Validation and Iteration are performed to refine the system based on user feedback and performance metrics.

By completing these tasks, we will address the identified challenges, such as data variability, overfitting, and the complexity of translating technical outputs to user-friendly formats. The successful execution of this plan will bring us closer to our goal of creating a tool that not only assesses cleanliness but also provides meaningful insights into the psychological well-being associated with living spaces.

6. Deliverables

6.1. Anticipated Outcomes, Potential Impact, and Deliverables

Upon successful completion, this project will result in a tool capable of evaluating indoor spaces for cleanliness. At its core, there is a machine learning model, trained on a dataset, that classifies spaces as either clean or messy. This approach represents an application of deep learning techniques to assess the organization of indoor environments.

The project currently consists of an adapted ResNet50 model, trained using PyTorch, that can analyze images of rooms and output a confidence score indicating whether the space is messy or clean. The model runs on 'mps' (Metal Performance Shaders) for macOS systems. Additionally, a simple graphical user interface (GUI) has been developed to allow users to input images and receive the model's predictions.

While the current scope is limited to binary classification of cleanliness, this project lays the foundation for potential future expansions. With further development, the model could be extended to consider more nuanced aspects of indoor environments, such as the psychological implications of space organization on well-being. This work represents an initial step towards merging deep learning techniques with environmental psychology, paving the way for more sophisticated applications in this domain.

The project's deliverables include the trained ResNet50 model, the GUI software interface for environmental assessment, technical documentation, and a final report. While the current state of the project may not fully realize the envisioned academic and commercial implications outlined in the original description, it serves as a proof-of-concept and a steppingstone for future research and development in this area.

6.2 Metrics, Milestones, and Measures of Success

1. **Model Accuracy**: The ResNet50 model currently scores 96.95% accuracy in correctly classifying images as clean or unclean on our test dataset.
2. **Model Precision and Recall**: Precision and recall metrics for the model both score 97%, ensuring that it is not only accurate overall but also effective in identifying true positives and true negatives.
3. **User Interface (UI) Responsiveness**: The user interface for the application loads and respond to user inputs within 1 second, ensuring a smooth user experience.

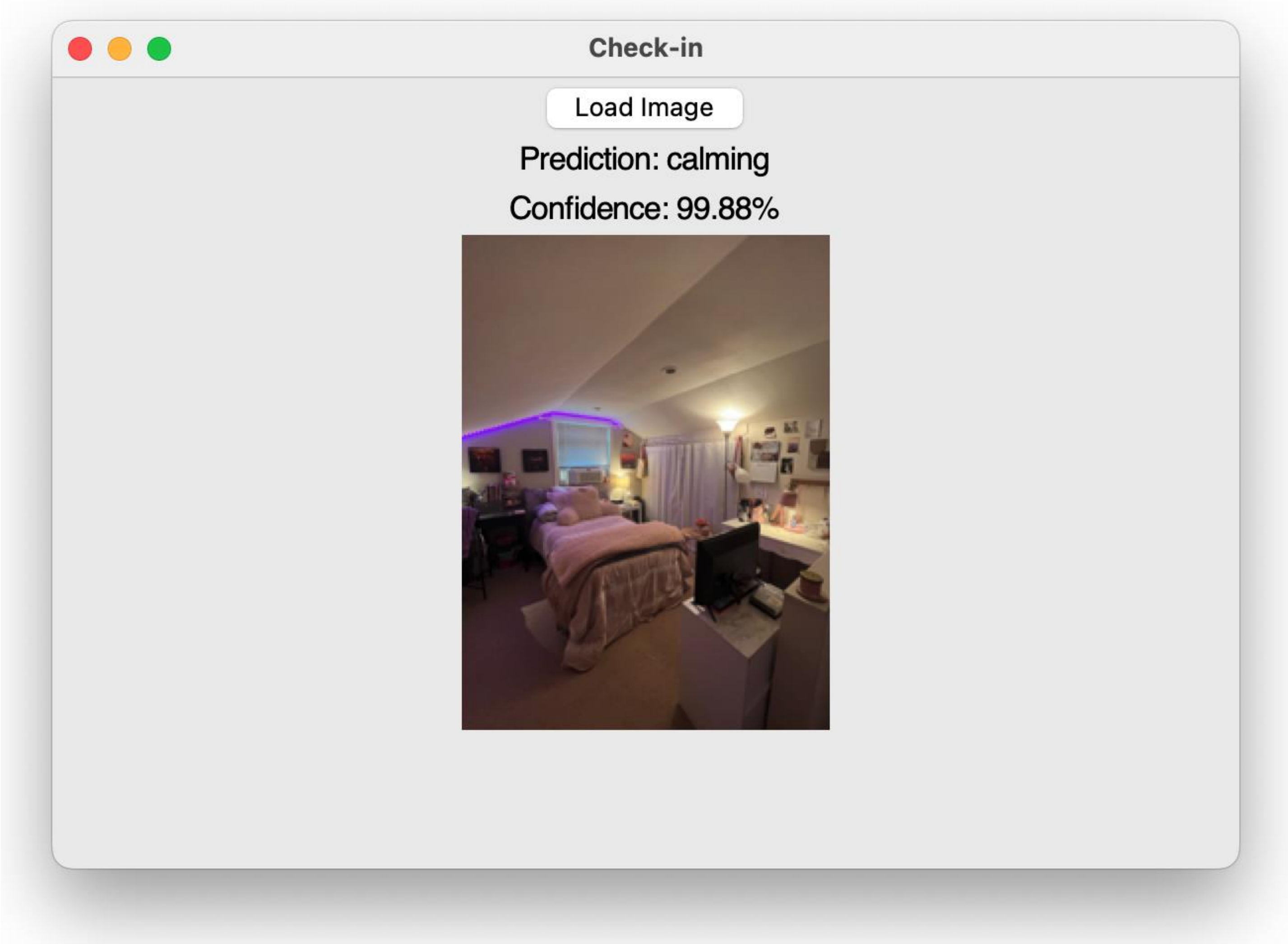

Figure 9: Screenshot of the Check-in application interface showcasing its functionality. A user has uploaded an image of their room, and the system has provided a 'calming' prediction with a high confidence level of 99.88%. This visual feedback is part of Check-in's user-friendly approach to assess environmental influence on mental well-being, exemplifying the application's ability to analyze and interpret space for therapeutic impact.

4. **Reduction in User Error Rate**: Post-deployment, the error rate in user operations should be less than 5%, showing that the interface is intuitive and well-designed.
5. **Data Processing Time**: The system processes and classifies a new image in under 2 seconds, making the tool efficient for real-time use.
6. **Model Training Time**: Completes the full training cycle of the model on the dataset within 48 hours, ensuring efficiency in the use of computational resources.

7. **Dataset Diversity**: The training dataset covers at least 300 unique indoor environments to ensure t

```
Accuracy: 96.95%
Confusion Matrix:
[[888  32]
 [ 26 958]]
Classification Report:
              precision    recall  f1-score   support

           0       0.97      0.97      0.97       920
           1       0.97      0.97      0.97       984

    accuracy                           0.97      1904
   macro avg       0.97      0.97      0.97      1904
weighted avg       0.97      0.97      0.97      1904
```

Figure 10. This screenshot showcases the performance metrics of the Check-In model on the test dataset. The accuracy is noted at 96.95%, with the confusion matrix displaying true and false positives and negatives. The classification report details the precision, recall, and F1-score, all indicating a high level of model performance with balanced support for both classes. This indicates the model's effectiveness in distinguishing between different environmental conditions affecting mental health.

6.2. Future Work

As we wrap up this phase of our project, it's clear that the journey doesn't end here. The groundwork we've laid with our model and the insights gained from assessing the psychological impact of room cleanliness have opened new avenues for exploration. Looking ahead, we could deepen our analysis by integrating additional environmental factors—like room objects and color schemes—that could further influence well-being. We aim to refine our model's predictive power and extend its applicability to broader settings, including workplaces and educational environments.

We invite the academic and tech communities to join us in this endeavor. Whether it's contributing to the dataset, refining the algorithms, or exploring new domains where this technology could make a difference, there's a wealth of opportunities to expand the boundaries of what we've started. Together, we can turn these initial findings into actionable solutions that improve living spaces and, ultimately, well-being on a global scale. Let's build on this momentum and push the limits of how machine learning can enhance our understanding of the spaces we inhabit.

7. Qualifications of the Project Team

I am Jordan White, currently a senior at the University of Washington, pursuing a degree in Electrical and Computer Engineering. Leading this ambitious project under the guidance of Sep Makhsous, my expertise lies primarily in machine learning and image processing—fields that are central to the development and success of this endeavor. My academic training and hands-on projects during my undergraduate studies have equipped me with the skills necessary to tackle the technical challenges this project presents.

Sep Makhsous serves as my mentor and advisor, bringing a wealth of knowledge and experience in advanced computing and data analytics. His guidance is instrumental in steering the project towards its scientific and practical goals. Together, we combine rigorous academic training and a passion for leveraging technology to solve real-world problems, aiming to make significant contributions to the field of environmental psychology and machine learning.

8. Conclusions

To conclude, it's evident that the intersection of machine learning and environmental psychology holds much potential for enhancing our understanding of how indoor spaces affect our well-being. The progress we've made with our ResNet50-based model has not only validated our initial hypotheses but also set the stage for further exploration and development. Moving forward, we're excited to go deeper into the nuances of this relationship, refining our tool to offer even more precise assessments and actionable insights. Our journey is just beginning, and we invite the community to join us in this exciting endeavor, where each step forward can contribute to healthier, more harmonious living and working environments.

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