



# Uncertainty-Aware Personal Assistant for Making Personalized Privacy Decisions

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Many software systems, such as online social networks, enable users to share information about themselves. Although the action of sharing is simple, it requires an elaborate thought process on privacy: what to share, with whom to share, and for what purposes. Thinking about these for each piece of content to be shared is tedious. Recent approaches to tackle this problem build personal assistants that can help users by learning what is private over time and recommending privacy labels such as private or public to individual content that a user considers sharing. However, privacy is inherently *ambiguous* and highly *personal*. Existing approaches to recommend privacy decisions do not address these aspects of privacy sufficiently. Ideally, a personal assistant should be able to adjust its recommendation based on a given user, considering that user's privacy understanding. Moreover, the personal assistant should be able to assess when its recommendation would be uncertain and let the user make the decision on her own. Accordingly, this article proposes a personal assistant that uses evidential deep learning to classify content based on its privacy label. An important characteristic of the personal assistant is that it can model its uncertainty in its decisions explicitly, determine that it does not know the answer, and delegate from making a recommendation when its uncertainty is high. By factoring in the user's own understanding of privacy, such as risk factors or own labels, the personal assistant can personalize its recommendations per user. We evaluate our proposed personal assistant using a well-known dataset. Our results show that our personal assistant can accurately identify uncertain cases, personalize them to its user's needs, and thus helps users preserve their privacy well.

CCS Concepts: • **Security and privacy** → **Privacy protections**;

Additional Key Words and Phrases: Privacy, uncertainty, online social networks

## ACM Reference format:

Gonul Ayçi, Murat Sensoy, Arzucan Özgür, and Pinar Yolum. 2023. Uncertainty-Aware Personal Assistant for Making Personalized Privacy Decisions. *ACM Trans. Internet Technol.* 23, 1, Article 13 (March 2023), 24 pages. <https://doi.org/10.1145/3561820>

This work was done before M. Sensoy joined Amazon Alexa AI.

G. Ayçi was supported by the Scientific and Technological Research Council of Turkey (TÜBİTAK) and the Turkish Directorate of Strategy and Budget under TAM project number 2007K12-873. This research was partially funded by the Hybrid Intelligence Center, a 10-year program funded by the Dutch Ministry of Education, Culture and Science through the Netherlands Organisation for Scientific Research (<https://hybrid-intelligence-centre.nl>).

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1533-5399/2023/03-ART13 \$15.00

<https://doi.org/10.1145/3561820>

## 1 INTRODUCTION

Collaborative systems, such as **online social networks (OSNs)**, enable users to share content with others. With the plethora of online content that is being shared, users are faced with the task of *managing* their privacy. Whenever a user is sharing content, she needs to think through whom the content is shared with, whether the content contains elements that would jeopardize her privacy, and so on. Some systems provide settings to configure sharing behavior (e.g., images can be shared only with friends). However, not all images are the same. For example, a user might be comfortable sharing a landscape image publicly, whereas she might prefer a family image to be shown only to friends. With current systems, identifying whether an image contains certain aspects that could be considered private is left to the user. Moreover, the content may be shared by the user herself and others. For a user to decide whether her privacy is being violated, she needs to check the contents related to her individually. This is obviously time-consuming and error-prone. Ideally, a personal assistant (software) could help the user make decisions by signaling whether the content could be private.

Personal assistants help their users make decisions to ease their online interactions. Personal assistants have been used to help users in various tasks, including time management [29], smart homes [6], voice assistance [12], and so on. Recently, personal assistants have been used for helping users manage their privacy online. Kökciyan and Yolum [20] develop personal assistants to detect privacy violations in OSNs on behalf of their users. They assume that the personal assistant has access to users' privacy preferences through elicitation. Using these preferences and a domain ontology, the personal assistant computes whether others in the OSN share content about the user against her preferences. Kekulluoglu et al. [18] and Such and Rovatsos [37] develop techniques to help users reach privacy decisions when a content being shared is owned by multiple users, such as a group image. Both approaches assume that the personal assistants of the users know the privacy preferences of the users and then they apply negotiation techniques to enable the personal assistants to reach a sharing decision that both users are comfortable with.

Because many approaches depend on using users' privacy preferences, there is a tremendous need to learn users' privacy preferences accurately. If a personal privacy assistant can represent the privacy expectations well, then these privacy assistants can help the users in privacy dealings, such as warning the user when the user attempts to share a private content, negotiate with other users on behalf of the user, and so on.

Learning privacy preferences of a user resembles a classical **machine learning (ML)** problem; however, there are two properties of privacy that make the problem difficult. First, privacy by definition is ambiguous, making it challenging to specify. This makes the pattern that is searched malleable. Second, the users themselves are not always certain about their own privacy preferences and may change their preferences based on other motives [1]. For these reasons, using a traditional predictive model is unreliable, as the cost of making a wrong privacy decision is high.

Ideally, the personal privacy assistant should adhere to the followings properties:

- *Unobtrusive*: The privacy assistant should learn from the sharing behavior of the user without interrupting the user (e.g., asking the user what to share or not) as well as without requiring additional information about the user or the content, such as age or occupation of the user or the tags of a content. Thus, the privacy assistant should only consult the user if necessary.
- *Uncertainty-aware*: As mentioned earlier, privacy decisions are many times ambiguous. A personal privacy assistant may not always be able to decide if a content is private or not for the user. The assistant should be uncertainty-aware of this uncertainty and be able to say "I don't know" rather than making an uncertain decision. Hence, it should let the user know that it is uncertain and delegate the decision back to the user.

- *Personalized*: There are two aspects of personalization that are important for the personal assistant to consider. First, to be able to understand the privacy expectations of its own user. This is important because privacy is subjective and what one user considers private might not be private for another user. Second, each user has a different *risk* associated with making a wrong decision. The risk here refers to classifying a content as private when it should have been public and vice versa. For example, a user might prefer that the personal assistant be risk-averse and classify a content as public when there is even a slight chance that the user would prefer it private.

Existing privacy personal assistants that learn users' privacy preferences do not address the uncertainty of their predictions while making decisions [23, 27, 40] (see Section 2 for details). The idea of considering risk to personalize decisions has been used before but not been coupled with privacy decisions as we have done here [32]. Accordingly, this article proposes a personal privacy assistant (PURE) that helps its user to make privacy decisions in a personalized way, taking into account the ambiguity of privacy predictions. An important aspect of PURE is that it explicitly calculates the uncertainty of its decisions using **evidential deep learning (EDL)** [31], which quantifies the predictive uncertainty of **deep neural networks (DNNs)**. When PURE is uncertain of its decisions, it delegates the prediction back to the user. PURE uses publicly annotated dataset to create an initial model for privacy but also factors in the *persona* of a user: the person's understanding of risk, personally labeled data, and when she should be consulted. In this way, PURE behaves differently for each user to minimize the user's perceived risk of privacy violations. Moreover, PURE does not need to have access to any other private information of the user (e.g., personal details or usage patterns) or any of the users in the system, including the relations among users.

The rest of this article is organized as follows. Section 2 provides a detailed summary of related work in techniques and tools to help users manage privacy. Section 3 explains our approach in detail. Section 4 provides details on the evaluation setup. Section 5 evaluates the proposed approach on a widely used dataset and demonstrates the benefits of capturing and exploiting uncertainty. Finally, Section 6 concludes our work with pointers to future directions.

## 2 RELATED WORK

The literature on approaches that help users manage their privacy is broad. One of the earlier works is due to Fang and LeFevre [7], who introduce a wizard software based on an active learning paradigm. The wizard generates a privacy preference model using extracted features from visible data and communities, and also user input such as asking questions. The wizard recommends privacy preferences to users for different information items on their profiles, such as birthday, address, or telephone number. One of their key findings is that a user's social network structure is an important resource when modeling the user's privacy preferences. This idea has been exploited also by Kepez and Yolum [19], where they propose an ML-based model for image privacy prediction. Their framework is based on several attributes about posts such as the sharing time, the location, and the content of the post. They make use of the user's social network to improve prediction. Both of these approaches are important for the privacy prediction task because their approaches use information about the user, her network, and her posts to improve prediction. However, in situations where such external information is not available, there is still a need to make recommendations to the user based only on the content.

Squicciarini et al. [35] propose the **Adaptive Privacy Policy Prediction (A3P)** system that predicts a privacy policy for images based on the information available for a given user in the context of social networks. A3P needs a user to specify some privacy policies before making a prediction of privacy policies. When recommending a privacy policy for an image, A3P takes into

account significant resources for the privacy concept such as actual image content, metadata, and social circle. A3P consists of two main components: A3P-core and A3P-social. When a user uploads an image, the A3P-core classifies the image first based on their contents and then updates each category into subcategories based on their metadata (if it exists). Then, A3P-core either predicts a policy based on the historical behavior or invokes A3P-social. A3P-social finds a representative privacy policies using user's social circle. Although A3P achieves high accuracy, it makes use of information beyond the images themselves and does not attempt to capture the uncertainty in the prediction as we have done here.

Various approaches have exploited using textual and visual features to train classifiers. An earlier work is by Zerr et al. [45], where they identify that combination of textual and visual features produces the best performance in terms of prediction. However, they do not consider personalization or uncertainty. Tran et al. [41] propose a privacy framework called *Privacy-CNH* that consists of object and convolutional features using a **convolutional neural network (CNN)** for image privacy detection. Similarly, Squicciarini et al. [34] present a learning model to privacy labels of images for binary privacy labels as private and public as well as multi-class privacy labels such as *Only You* or *Family*. They show that combining SIFT (scale-invariant feature transformation) and tag features perform better than the other two or three combinations such as sentiment, RGB, or facial detection. The results of these approaches have been improved by Tonge and Caragea [40], who tackle the same problem using deep visual semantic and textual features, namely deep tags and user tags. While extracting deep features, they use pre-trained CNN architectures such as AlexNet [22], GoogLeNet [38], VGG-16 [33], and ResNet [13] with support vector machine classifiers for the privacy prediction task. Deep tags of images are top  $k$  predicted object categories that are extracted from pre-trained models. Using user-created tags, they create deep visual features by adding highly correlated tags to visual features extracted from the fully connected layer of the pre-trained models. Their results show that a combination of user tags and deep visual features from ResNet with the top 350 correlated tags yield the best performance. Moreover, based on their experimental results, fine-tuned networks perform better than learning models trained on the pre-trained features. Although their focus has been on classification alone, here we attempt to take into account both the uncertainty and the personalization associated with making privacy decisions, which is critically important for real-life use cases.

Alternative to approaches that use the image content, some recent approaches have used the tags associated with the content to predict privacy labels of images. Squicciarini et al. [36] introduce the Tag-To-Protect (T2P) system that automatically recommends privacy policies using the image tags and privacy policies. Their proposed system is useful for both newly uploaded images and cold-start problems when there are very few tags available. One of the prominent results from their experiment is that the prediction accuracy decreases when there is a large set of tags, because if the number of tags per image increases, finding a pattern becomes difficult. Kurtan and Yolum [23] propose an agent-based approach that predicts the binary privacy labels of images such as private or public using automatically generated content tags. The system keeps track of content being shared using tag tables. The internal tag table stores the data of privacy labels that are collected from images that the user shares herself. The external tag table stores the data collected from the images that the user's friends have shared with the user. Using metrics inspired by information retrieval, they define metrics to measure how informative a tag is to assess the privacy of an image. Contrary to previous approaches, this system performs well even the personal assistant has access to small data. However, they are not concerned about capturing the uncertainty explicitly or take into account personal risk factors as we have done here.

An alternative set of approaches makes use of groups of users, considering various similar aspects among users to make recommendations. Misra and Such [27] develop PACMAN, a personal

assistant that recommends access control decisions. Their approach is based on identifying communities (e.g., friend networks) from the OSN structure of a user and information about the content such that users manually select tags to extract information about the content. Zhong et al. [47] propose the Group-Based Personalized model for an image privacy classification task. Their proposed model learns privacy groups and private content types. Using additional profile information (e.g., gender or age range), they estimate new users' privacy decisions. They evaluate their proposed model on a randomly selected subset of the PicAlert dataset [45] by first extending it with by adding demographics and social network usage information. They show that the Group-Based Personalized model (with profile information) outperforms several baselines such as support vector machine approaches.

Fogues et al. [8] present a personal agent, SoSharP, that recommends sharing policies in multi-user scenarios. SoSharP uses contextual-based, user-based, preference-based, and group-based features. These features help provide personalized recommendations in three rounds. SoSharP makes recommendations to each user by using context-based and user-based features in the first round. It moves to the second round if at least one user has not accepted sharing policy. It uses preference-based features in addition to the features used in the first round. In the final round, it makes a recommendation for all users by using group-based features. As a result of the last round, SoSharP recommends manual resolution if most of the users do not agree with the recommendation. Mosca and Such [28] also propose an agent, ELVIRA, for multi-user settings that benefits from recommending individual decisions to each user. Although we do not consider multi-user settings here, our work can be applied in multi-user settings to recommend privacy labels to each user before a group decision is taken.

Sensoy et al. [32] propose risk-calibrated evidential deep classifiers to make a better classification by decreasing the costs of misclassified predictions. They reformulate the EDL method to accomplish this goal. Their experiments show that the proposed Risk EDL method has lower misclassification costs compared to EDL, standard learning with cross-entropy loss, and cost-sensitive learning methods for the MNIST, FashionMNIST, and CIFAR10 datasets. They also report that their method is robust for out-of-distribution samples. However, they do not apply their model on privacy as we have done here.

Yu et al. [43] propose an algorithm to recommend privacy labels of images in OSNs. Their recommendation algorithm takes into account two approaches: an image content sensitiveness and trustworthiness of a user. To train a tree classifier, the algorithm uses feature-based and object-based approaches for the image content sensitiveness and characterization of users' trustworthiness based on social behaviors. Through extensive evaluations over user study and two publicly available datasets (e.g., PicAlert and MIRFLICKR), they have shown that the proposed algorithm is effective. However, PURE is both an uncertainty-aware and risk-aware model for predicting privacy labels of images. It can achieve high performance without using the profile information of a user, the user's social connections, or organizing different types of image privacy concerns.

Kökciyan and Yolum [21] propose an approach, TURP, that manages the trustworthiness of information sources, **Internet of Things (IoT)** devices, for making context-based privacy decisions. They represent IoT devices and users as software agents. Each agent has a confidence value when it shares information with another agent. In the beginning, each device has the same trust value. These values are updated based on feedback that is given from multiple agents. TURP uses Disjunctive Datalog while reasoning about information collected from multiple agents. It would be interesting to couple TURP with our proposed approach in an IoT context so that the privacy decisions are augmented with trust.

Jiao et al. [15] design a system, IEye, that provides a personalized and interpretable privacy model. They first extract features from images and use multi-layered semantic graphs for feature



representations of images. Then, they learn personalized privacy rule sets from images using the rule-based classification algorithm RIPPER. They compare their methods with SIFT and deep features extracted from pre-trained networks AlexNet, VGG16, and ResNet152. They evaluate the performance of their method IEye on the PicAlert dataset and a small dataset called *PPP*, which consists of 8,744 images of 20 users. IEye has a better accuracy result on the *PPP* dataset than the baseline approaches. However, the proposed method is not better than deep features for the PicAlert dataset.

Yuan et al. [44] propose a context-dependent and privacy-aware model for images. The model uses the image's content and contextual information about the image and a specific requester. Their proposed framework first extracts general features (e.g., people, location, time, activity) and contextual features of the sender's images. The system collects information about the sender's preferences by asking questions to the sender in different scenarios. It trains a classifier on this information. When a requester exists, the classifier makes a decision based on the sender's information and the requester's contextual features. They then evaluate their approach to conducting a user study on manually annotated images with personalized contextual sharing decisions through the *ProShare S* application that they developed. However, they do not focus on uncertainty as we have done here.

Dammu et al. [3] develop a system for the image privacy prediction task. Their approach is capable of personalization, explainability, configurability, and customizable privacy labels. The system has four modules, such as object detection, location detection, object localization, and explicit content extraction. The decision network aggregates outputs of modules for personalized privacy predictions. This comprehensive approach help make personalized prediction of the image labels. To provide such a personalized system, their approach gets feedback from users for misclassified images. Because of the subjectivity privacy, asking users and using their explanations have an important role. However, it is not clear how this would scale in applications that use large image sets.

Han et al. [11] propose a method that uses multi-level and multi-scale deep representations for the image privacy prediction task. First, they obtain these deep representations in a CNN-based model. Then, they propose two feature aggregation models, such as Privacy-MSML and Privacy-MLMS, based on different aggregation strategies using Bi-LSTM and self-attention. They evaluate the performance of proposed models on a subset of the PicAlert dataset. They show that their proposed aggregation models yield better performance by F1-score compared with ResNet-18, CNN-RNN, and concatenated multi-level features. However, they are not concerned with capturing the uncertainty in their predictions as we have done here.

Liu et al. [25] present problems, challenges, approaches, and future directions of ML in privacy. By taking into account the roles of ML in privacy, they divide existing works into three categories; private ML, ML-enhanced privacy protection, and ML-based privacy attacks. In the first category, the aim is to develop a private ML system including model parameters, training/test datasets, and predictions. Differential privacy is one of the popular ML solutions that is capable of protecting the privacy of the individual data items [5]. In the second category, ML approaches are used to make decisions for content to preserve privacy and predict information leakage. For instance, ML-based models predict applications' privacy risks, identify contents' sensitive information, and learn users' privacy preferences. The third category presents the importance of ML attack models, including re-identification and inference attacks. Preserving privacy under such attacks becomes more challenging with the rapid increase in the usage of OSNs and the recent advances in DNNs. However, DNNs are vulnerable to adversarial perturbation. Goodfellow et al. [10] propose the Fast Gradient Sign method to generate adversarial examples. Differently from such kind of attacks, Miao et al. [26] introduce the controlled (protected) information stealing attack. They explain the phases of ML-based attack methodology, discuss the challenges of such attacks, and share the defense

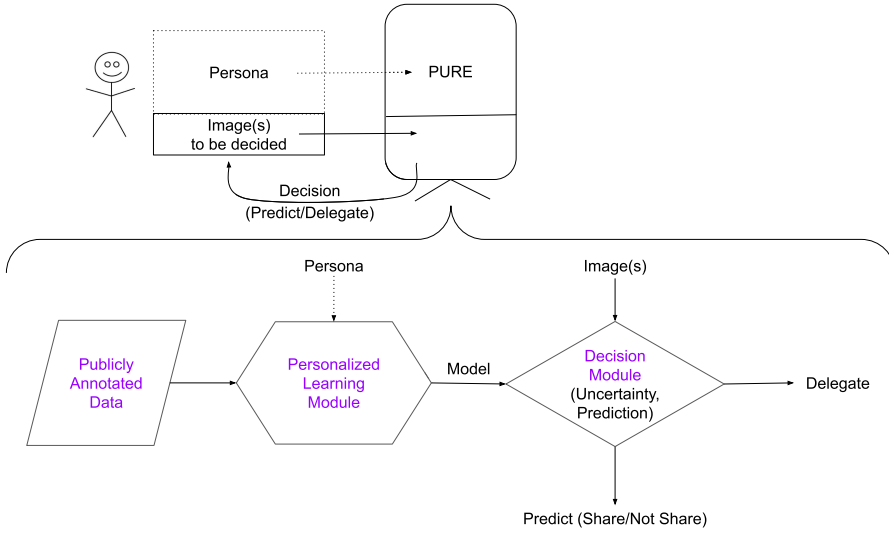


Fig. 1. System overview schema. The OSN user has a personal assistant PURE. She can share persona with her personal assistant. First, PURE has *Publicly Annotated Data* collected from different annotators available in the PicAlert dataset. It learns privacy preferences using visual features in the *Learning Module* and produces *Model*. While learning, the user can share her persona type (i.e., sensitive, semi-sensitive, and non-sensitive) that she can be sensitive about classifying private images as public or not. In this case, the personal assistant is risk-averse. Moreover, the user can share personal data that the user herself annotates, allowing learning the user’s privacy preferences. Then, PURE makes privacy decisions for its user’s content (e.g., image) in the *Decision Module*. While making a prediction for each image, it also generates an uncertainty value for that prediction. To reach a privacy decision, PURE decides whether to use prediction results (i.e., *share* or *not share*) or to delegate the decision to the user (i.e., *delegate*) by comparing the uncertainty value with the threshold received from its user.

mechanisms. The work that we present here falls into the second category such that we use ML methods to enhance privacy protections.

### 3 PURE: UNCERTAINTY-AWARE PRIVACY ASSISTANT

We envision PURE to work side-by-side with its user when the user is about to share content and help its user make privacy decisions (Figure 1). PURE uses a learning model that predicts a privacy label of a given image either *private* or *public*. The image is considered to be private if it belongs to the private sphere or contains objects that the user cannot share with the world and public otherwise. Figure 2 shows examples of images annotated as private and public in the PicAlert dataset by two different annotators.

PURE consists of two modules. The main module is the personalized learning module and serves as the core of the personal assistant. The purpose of this module is threefold. First, using publicly annotated data, it learns to classify images as private or public. Second, it quantifies uncertainties in predictions such that when it estimates a prediction to be highly uncertain, it can delegate the decision making to the user. Three, it incorporates the user’s expectations in privacy, as each user might have a different *persona* when it comes to how they would like to treat certain factors in the learning. The learning model uses EDL to realize these goals. The learning module produces a classification model that can label a given image and estimate the uncertainty in the prediction. Whenever a user provides personally labeled data, this module uses that to tune the personal

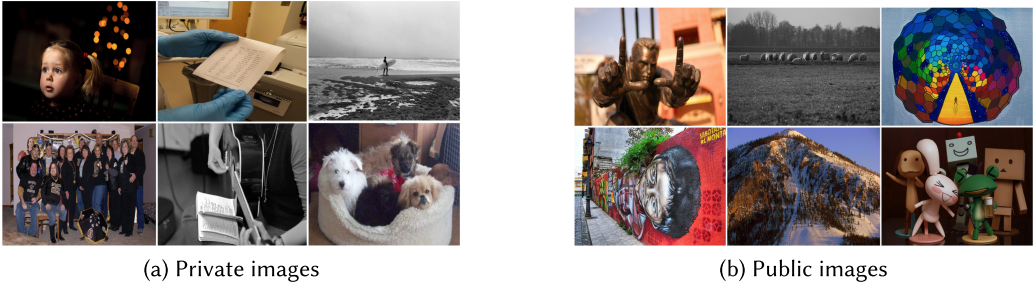


Fig. 2. Examples of images labeled as private and public by the annotators.

assistant using the images of the user. This is important because privacy is inherently subjective and the publicly annotated dataset that is used for the learning module may not reflect the privacy expectations of the user. Moreover, due to the subjectivity, PURE might assign high uncertainty to some images. By fine-tuning using personal data, we aim to decrease the uncertainty that PURE might observe with some images. The second module is the decision making module. When a user needs to make a privacy decision, this is the module that is invoked. This module obtains a prediction and an uncertainty value from the model. Each user defines for themselves when to let PURE make a decision and when they would want to be involved. By setting a threshold, a user can choose to decide on the privacy labels when the uncertainty is above the set threshold. Otherwise, the prediction of the model is assigned as the label.

### 3.1 Learning Privacy Labels with Uncertainty

EDL [31] is based on the Dempster-Shafer theory of evidence [4] and subjective logic [16] to quantify uncertainty in classification tasks. Subjective logic expresses degrees of uncertainty through subjective opinions. Each subjective opinion corresponds to a Dirichlet distribution, a conjugate prior for the categorical distribution. For a binary proposition (e.g., the image  $x$  is private), the subjective belief of a personal assistant for the truth of this proposition [17, 46] is represented as a binomial opinion, which corresponds to a Beta distribution—a special form of Dirichlet distribution. Since privacy classification is a binary classification task, a personal assistant's belief for an image to be private is represented as a binomial subjective opinion. A binomial subjective opinion for the classification can be represented as a Beta distribution. That is why, in this section, we will introduce EDL using Beta distributions. Beta probability density function is expressed as

$$\text{Beta}(p|\alpha, \beta) = \frac{p^{\alpha-1}(1-p)^{\beta-1}}{B(\alpha, \beta)}, \quad (1)$$

where  $B$  is the multivariate beta function [31] and  $[\alpha, \beta]$  are the parameters of the Beta distribution. In Equation (1),  $p$  is the Bernoulli probability that the binary proposition is true (e.g., the probability that the image  $x$  is private). A personal assistant has a belief ( $b$ ) for the proposition that *the image is private*, a disbelief ( $d$ ) for the same proposition, and an uncertainty ( $u$ ) that represents the inability to classify the image accurately. The personal assistant's uncertainty about an image may be due to the noise in the image or the lack of training data with similar images. We can calculate these quantities as

$$b = \frac{\alpha - 1}{\alpha + \beta}, \quad d = \frac{\beta - 1}{\alpha + \beta}, \quad \text{and} \quad u = \frac{2}{\alpha + \beta},$$

where  $b, d, u > 0$  and  $b + d + u = 1$ . Furthermore,  $\alpha - 1$  and  $\beta - 1$  are referred to as the evidence for and against the proposition: *the image is private*. Let us note that  $u$  is maximized when  $\alpha = \beta = 1$ ,



corresponding to the uniform Beta distribution. We can also refer to them as the evidence for the *private* and *public* categories in the classification of the image.

The Beta distribution provides a probability distribution over  $p$ —the probability that the given image is private. However, in classification tasks, we need a predictive categorical distribution to decide. For this purpose, we use the expected value of the Beta distribution, which is calculated as follows:

$$\bar{p} = \int_0^1 p \left( \frac{p^{\alpha-1}(1-p)^{\beta-1}}{B(\alpha, \beta)} \right) dp = \frac{\alpha}{\alpha + \beta}. \quad (2)$$

The aforementioned calculations of belief masses and uncertainty are based on the parameters of the corresponding Beta distribution. To model belief masses and learn Beta distribution parameters, EDL modifies a vanilla neural network for classification by replacing its softmax layer with a non-negative activation function such as *ReLU*, *softplus*, and *exponential* functions. In our classification problem, we have two categories: *private* and *public*. Given a sample image  $x$ , we can use any neural network with two logits outputs:  $o_0(x)$  and  $o_1(x)$ , one for each category. Then, we use the exponential function to calculate evidence for each category as follows:  $e_{pub}(x) = \exp(o_0(x))$  and  $e_{pri}(x) = \exp(o_1(x))$ , which represent the evidence for the public and private categories, respectively. The Beta distribution parameters  $\alpha$  and  $\beta$  for the classification of the image  $x$  are calculated as  $\alpha(x) = e_{pri}(x) + 1$  and  $\beta(x) = e_{pub}(x) + 1$ , respectively.

Let  $y \in \{0, 1\}$  represent the category index of the sample image  $x$ . In **standard neural networks (SNNs)** for binary classification, the sigmoid function is used to calculate  $p(x) = P(y = 1|x)$ —that is, the probability that  $x$  is from category  $y = 1$ . Then, the binary cross-entropy loss is calculated as follows:

$$y \log(p(x)) + (1 - y) \log(1 - p(x)).$$

There are also other loss functions for classification, such as the Brier score, which is defined as

$$[p(x) - y]^2 + [1 - p(x) - (1 - y)]^2. \quad (3)$$

The Brier score is a proper scoring function and is frequently used to measure the accuracy of probabilistic predictions. Unlike vanilla neural classifiers, we do not predict  $p(x)$  directly, so we cannot directly use any of these loss functions. However, we predict its Beta distribution *Beta* ( $p(x)|\alpha(x), \beta(x)$ ), hence we may calculate the expected loss by integrating out  $p(x)$  in the classification loss of our choice. We can calculate the expected Brier score for privacy classification as follows:

$$\mathcal{L}(x, y) = \int_0^1 [p(x) - y]^2 + [1 - p(x) - (1 - y)]^2 \frac{p(x)^{\alpha(x)-1}(1-p(x))^{\beta(x)-1}}{B(\alpha(x), \beta(x))} dp(x), \quad (4)$$

which has the following closed-form solution:

$$\mathcal{L}(x, y) = [\bar{p}(x) - y]^2 + [1 - \bar{p}(x) - (1 - y)]^2 + 2 \frac{\bar{p}(x)(1 - \bar{p}(x))}{\alpha(x) + \beta(x) + 1}, \quad (5)$$

where  $\bar{p}(x)$  is the expectation of  $p(x)$  and calculated as  $\alpha(x) / (\alpha(x) + \beta(x))$  using Equation (2),

$$\mathcal{L}(x, y) = \int_0^1 \left[ y \log(p(x)) + (1 - y) \log(1 - p(x)) \right] \frac{p(x)^{\alpha(x)-1}(1-p(x))^{\beta(x)-1}}{B(\alpha(x), \beta(x))} dp(x), \quad (6)$$



Fig. 3. An example for predicting privacy labels of four images and quantifying uncertainty values for each prediction.

which has the following closed-form solution:

$$\begin{aligned} \mathcal{L}(x, y) = & y (\psi(\alpha(x) + \beta(x)) - \psi(\alpha(x))) \\ & + (1 - y) (\psi(\alpha(x) + \beta(x)) - \psi(\beta(x))), \end{aligned} \quad (7)$$

where  $\psi(\cdot)$  is the *digamma* function. We also add a regularizing term  $\mathcal{R}(x, y)$  to this loss.  $\mathcal{R}(x, y)$  is defined as follows:

$$\mathcal{R}(x, y) = \lambda_t \text{KL}[Beta(p(x); \bar{\alpha}, \bar{\beta}) \parallel Beta(p(x); 1, 1)], \quad (8)$$

where

- $t \geq 0$  is the index of the current training epoch,
- $\lambda_t = \min(1.0, t/10)$  is the annealing coefficient,
- $\text{KL}[\cdot \parallel \cdot]$  refers to the **Kullback-Leibler (KL)** divergence,
- $\bar{\alpha} = \alpha(x)^{1-y} = (e_{pri}(x) + 1)^{1-y}$ ,
- $\bar{\beta} = \beta(x)^y = (e_{pub}(x) + 1)^y$ , and
- $Beta(p(x); 1, 1)$  is the uniform Beta distribution.

Let us note that  $\bar{\alpha}$  and  $\bar{\beta}$  do not contain any evidence supporting the true category of the sample image. In other words,  $\alpha(x)^{1-y}$  becomes 1 if the image is private ( $y = 1$ ), and  $\beta(x)^y$  becomes 1 when the image is public ( $y = 0$ ). As a result, the KL divergence term is minimized when the network does not produce any evidence for the wrong category. Hence, this regularization term minimizes the evidence generated by the network for the wrong category and increases the predictive uncertainty for the misclassified samples [31].

*Example 1.* Let us assume that Alice is an OSN user. She has four different images. She needs to decide which images should be shared as public and which should be shared as private. Figure 3 represents an example for predicting privacy labels (e.g., private or public) of her images and quantifying uncertainty values for each prediction. In Figure 3, the first and the fourth images are public, and the other two are private. As shown in Figure 3, PURE predicts a label for each image as well as an uncertainty value. When producing an answer, it checks its uncertainty value and threshold to decide to answer with its current predicted label or delegate the decision to its user. If the threshold here is 0.7, it will put forward its predictions for images 2 and 3 (as these have uncertainty values 0.1 and 0.5, respectively) and delegate image 1 and 4 to its user. With this setup, PURE would have correctly classified image 2, but image 3 would have been misclassified. It would have delegated image 1 that it would have failed on, but it would have also been delegated image 4 to the user that this image is correctly classified.

### 3.2 Personalizing Privacy

Since privacy is inherently subjective, it is important to incorporate personal traits of the user into the decision making. We consider three aspects of a user that should be factored into the decision making: (1) perception of risk, (2) personal categorization, and (3) preference to be involved.

*Perception of risk.* While the personal assistant is making decisions, it is possible that it makes a prediction error. It is possible that for some users misclassifying a private image as public may lead to less desirable consequences than misclassifying a public image as private. For some others, there might not be a difference. Furthermore, the cost of different misclassifications may be significantly different for two different users. To avoid mistakes that are deemed risky for the user, the system needs to incorporate the risk perception of the user into account.

Typically, vanilla neural networks do not differentiate this significant difference and consider all mistakes as equal. To overcome this, here we introduce a user-dependent risk matrix, which is an asymmetric non-negative square matrix  $R \in [0, \infty)^{2 \times 2}$ . Each value  $R_{ij}$  in  $R$  represents the user's cost when the classifier assigns an image from category  $i$  to category  $j$ . There is no cost for the user for correct classification, hence  $R_{ij} \geq R_{ii} = 0$ .

There may be different ways of incorporating the user's risk of misclassification into the training of evidential classifiers. In this article, we propose scaling misleading evidence in the KL divergence term by modifying  $\bar{\alpha}$  and  $\bar{\beta}$  as follows:

$$\begin{aligned}\bar{\alpha} &= (R_{01}e_{pri}(x) + 1)^{1-y} . \\ \bar{\beta} &= (R_{10}e_{pub}(x) + 1)^y .\end{aligned}$$

This allows us to increase the KL divergence further when evidence for high-risk categories are produced. The PURE gets  $R$  from its user and can learn how to generate evidence for each category based on the personalized cost of making misclassification. If the user is sensitive about classifying private images as public, the personal assistant also becomes sensitive and avoids generating evidence for the private category for equivocal and ambiguous images:

- (1) Scaling misleading evidence in the KL divergence term by modifying  $\bar{\alpha}$  and  $\bar{\beta}$  as follows:

$$\begin{aligned}\bar{\alpha} &= (R_{01}e_{pri}(x) + 1)^{1-y} . \\ \bar{\beta} &= (R_{10}e_{pub}(x) + 1)^y .\end{aligned}$$

This allows us to increase the KL divergence further when evidence for high-risk categories is produced.

- (2) Regularizing the amount of misleading evidence directly using the risk of misclassification:

$$(1 - y)\bar{p}(x)R_{01}e_{pri} + y(1 - \bar{p}(x))R_{10}e_{pub},$$

where  $\bar{p}(x)$  is the predictive categorical distribution calculated as  $\bar{p}(x) = \alpha(x)/(\alpha(x) + \beta(x))$ . This term will be added to the aforementioned loss:  $\mathcal{L}(x, y) + \mathcal{R}(x, y)$ .

*Example 2.* If for a user there is no difference between the misclassification of private and public images, then PURE makes predictions as shown in Figure 3. However, assume that Alice is more sensitive about classifying a private image as public. By reflecting this in the  $R_{ij}$  score, PURE predicts privacy labels of images and quantifies uncertainties for each prediction as shown in Figure 4. Notice that the uncertainty values, as well as the predicted labels, have changed compared to Figure 3. With the uncertainty threshold still set to 0.7, PURE will delegate the same set of images (1 and 4) and answer images 2 and 3. Image 3 has been correctly classified this time. This is a

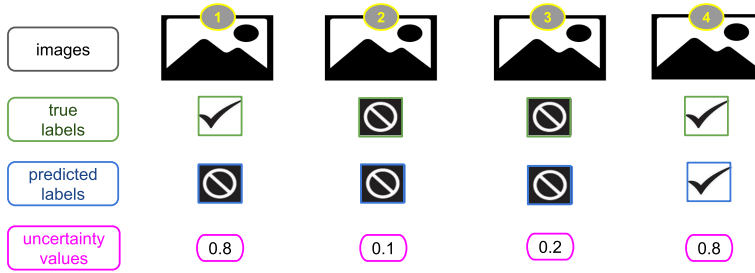


Fig. 4. An example for predicting privacy labels of four images for a sensitive user and uncertainty values for each prediction.



Fig. 5. An example for predicting privacy labels of four images by fine-tuning using personal data and uncertainty values for each prediction.

by-product of the fact that PURE chooses to classify more images as private to avoid the potential risk associated with classifying private images as public.

*Personal categorization.* Another aspect of personalization is to understand what images a particular user finds private or public. One way of understanding this is to ask the user about privacy preferences. However, there is long-standing evidence that users are not good at articulating what they find private. Moreover, their actions are not always in line with what they claim to be private. Thus, a better way of understanding what is private for a user is to utilize personal data: images that are labeled by the user herself.

PURE makes use of this to fine-tune the model it generates. After PURE is trained on publicly annotated data, the user's own labeled data is to adjust the uncertainties in the model. An important contribution of this would be that the uncertainty in certain images drop such that model is more certain of its prediction.

*Example 3.* If PURE uses publicly available data and if Alice is a sensitive user about classifying a private image as public, PURE makes predictions in Figures 3 and 4, respectively. Moreover, if Alice shares her personal data that has been annotated by her, PURE will predict privacy labels and uncertainty values for each prediction as shown in Figure 5. If uncertainty threshold is still 0.7, PURE will delegate image 1 to Alice and correctly classify images 2, 3, and 4 (as these have uncertainty values 0.1, 0.2, and 0.3, respectively). Since image 4 would have been correctly predicted with a lower uncertainty value, it would have not delegated to the user. Thus, all classifications would be correct this time, and PURE would ask its user less.

*Preference to be involved.* The final part of personalization is to understand how much a user wants to be involved in the decision making. Recent work [2] in HCI shows that although some users

are happy to have privacy decisions taken by their privacy assistants on their behalf, some users would rather be in the loop. Moreover, this is not always a binary decision in the sense that with some decisions the user might want to be involved while with others she might not. We capture this preference to be involved in the decision making process explicitly using a threshold value  $\theta$ . Whenever PURE is asked to label an image, in addition to a prediction, PURE also provides a level of uncertainty. When PURE has an uncertainty above  $\theta$ , it delegates the decision making back to the user. Since  $\theta$  can be configured by the user herself, it enables the user to select a level of involvement, where  $\theta = 1$  would mean letting PURE do all the decisions, and where  $\theta = 0$  would mean overseeing all of the decisions. During our experiments, we discuss having  $\theta = 0.7$  as a working setting to capture user involvement only when PURE has high uncertainty.

## 4 EVALUATION

We evaluate the performance of PURE in terms of its contribution to preserving privacy. Specifically, we aim to answer the following research questions:

- RQ1:** Does PURE capture the privacy ambiguity through its modeling of uncertainty and by delegating ambiguous cases to the user, and can PURE increase its privacy prediction accuracy?
- RQ2:** Does PURE capture uncertainty adequately and outperform existing models that capture uncertainty?
- RQ3:** Can PURE enable personalization of privacy by incorporating privacy risks and personal data of the user so that the accuracy is improved for the user while the number of delegated decisions decrease?

It is important to be able to answer RQ1 affirmatively because capturing the ambiguity is the key for PURE to choose when to consult its user. Ideally, uncertain images should be delegated to the user for a decision, and certain images should be answered by PURE. As a result, if we consider only the certain images that PURE makes a prediction on, we would expect to obtain a higher accuracy than the overall accuracy. RQ2 investigates the dynamics between uncertainty and making prediction errors and questions whether alternative formulations of uncertainty such as an SNN or well-known uncertainty quantification methods such as **Monte Carlo (MC)** Dropout and Deep Ensemble would suffice. Finally, RQ3 explores if and to what extent personalization of PURE helps users, either in terms of the accuracy they obtain or the number of images they have to decide.

### 4.1 Dataset

To evaluate our work, we selected a balanced subset of the PicAlert dataset [45]. PicAlert is a well-known benchmark dataset for the privacy prediction problem for images that contains Flickr images that are labeled as *public* or *private* by external viewers. These images are the most recently uploaded images for 4 months in 2010 and labeled by 81 users between 10 and 59 years of age with varied backgrounds; 17% of the images in this dataset have conflicting labels from annotators. We consider an image as public if all of the annotators have annotated it as public and private if at least one annotator has annotated it as private. The subset we work with contains 32K sample that are labeled as *public* and *private*. It is split into *Train* and *Test* sets of 27K and 5K samples, respectively.

While the previous research aims at increasing the accuracy of the privacy prediction, additionally we focus on how to quantify the uncertainty in these predictions and exploit it to improve the user's privacy in the face of automated decisions.

### 4.2 Metrics

We evaluate the performance of our approach using two main metrics: (1) success of the model in terms of the standard metrics such as *Accuracy*, *F1-score*, *Precision*, and *Recall*, and (2) ability of the



Table 1. Performance of PURE Using Different Pre-Trained Models: ResNet50, InceptionV3, and VGG16

	<b>Accuracy</b>	<b>F1</b>	<b>Precision</b>	<b>Recall</b>
<b>ResNet50</b>	0.89	0.89	0.89	0.89
<b>InceptionV3</b>	0.89	0.89	0.89	0.89
<b>VGG16</b>	0.73	0.72	0.8	0.73

model to quantify its predictive uncertainty, which allows the improvement of the success metrics in (1) if quantified correctly and accurately.

We first evaluate our approach without considering personalization, hence the generated evidence is not weighted based on the perceived privacy risk of the user. Then, we extend our evaluations with the personalized risk matrices to see how our model adapts itself for users with different misclassification costs. We also extend evaluations with personal data that is annotated by a user to observe how PURE adapts and then asks less to its user. To evaluate the quality of the uncertainty estimates, we calculate the accuracy of the model only on the test samples for which the model's uncertainty is less than a given uncertainty threshold between 0 and 1. When the uncertainty threshold is 1, all test samples are considered in computing the accuracy (and other metrics like precision and recall); however, when the threshold is reduced to 0.5, predictions with uncertainty less than 0.5 are considered for the calculation.

### 4.3 Evaluation Setting

We use models that are pre-trained on ImageNet to extract features from images. We compare three popular deep architectures of CNNs: ResNet50 [13], InceptionV3 [39], and VGG16 [33] in terms of their performance. Table 1 shows the results of the comparison (*Accuracy*, *F1-score*, *Precision*, and *Recall*) of PURE using ResNet50, InceptionV3, and VGG16. ResNet50 and InceptionV3 pre-trained models yield better-performing models as compared to VGG16. ResNet50 avoids the network from the vanishing gradient problem. It has batch normalization layers that mitigate internal covariate shift. Because it enables more efficient training and performs well, while having fewer layers and parameters for other models with similar performance, we choose ResNet50 as our underlying architecture.

We use the ResNet50 architecture as our base neural network and replace its last layer (logits layer) with a densely connected layer with two outputs—one for each class (private and public). This architecture has 50 layers with residual connections. We implement our model using TensorFlow and initialize the network layers from the ResNet50 model and train 15 epochs on the PicAlert dataset using the Adam optimizer with a decaying learning rate initialized as  $1e - 5$ . ResNet50 accepts images with dimensions  $224 \times 224 \times 3$ , so we resize the images to these dimensions. The implementation used in this work is available at <https://git.science.uu.nl/ayci0001/PURE>.

## 5 EXPERIMENTAL RESULTS

We perform the following experiments with the mentioned dataset to answer our research questions.

*Performance of PURE.* We start by examining the accuracy of PURE, where we configure PURE to provide a label no matter what the uncertainty is. We experiment with using the entire available training data and compare it to cases where the training data is smaller.

Table 2 shows the overall performance of PURE. For instance, when we use all data while training, PURE obtains an accuracy of 0.89. PURE obtains an accuracy of 0.87 for 25% of training data. However, if PURE is trained on only 1% of data, the accuracy decreases to 0.55. Table 3 shows the

Table 2. Overall Results for PURE as Training Samples Are Reduced

	Overall			
Usage %	Accuracy	F1	Precision	Recall
<b>100</b>	0.89	0.89	0.89	0.89
<b>75</b>	0.88	0.89	0.88	0.88
<b>50</b>	0.88	0.88	0.88	0.88
<b>25</b>	0.87	0.87	0.87	0.87
<b>10</b>	0.79	0.78	0.82	0.79
<b>5</b>	0.66	0.62	0.76	0.66
<b>1</b>	0.55	0.44	0.69	0.55

Table 3. Results for the Private and Public Classes of PURE at Different Training Sample Rates

	Private			Public		
Usage %	F1	Precision	Recall	F1	Precision	Recall
<b>100</b>	0.89	0.91	0.87	0.89	0.87	0.92
<b>75</b>	0.88	0.91	0.87	0.89	0.86	0.92
<b>50</b>	0.88	0.92	0.84	0.89	0.85	0.92
<b>25</b>	0.86	0.91	0.81	0.87	0.82	0.92
<b>10</b>	0.75	0.92	0.63	0.81	0.72	0.95
<b>5</b>	0.49	0.94	0.34	0.74	0.6	0.98
<b>1</b>	0.19	0.85	0.11	0.68	0.52	0.98

performances of PURE for the private and public classes while using different amounts of data. For instance, PURE achieves an F1-score of 0.89 for each class when PURE uses all images in the training dataset. While training with 1%, PURE exhibits poor performance in terms of the F1-score, especially for the private class. If a user has only 10% of training data, PURE obtains an F1-score of 0.75 and 0.81 for the private and public classes, respectively. This is promising because it shows that even when there is limited training data, PURE can be useful.

Recall that an important aspect of PURE is that it can calculate uncertainty. Next, we look at the relation between uncertainty and accuracy to capture if PURE can represent uncertainty correctly. We have set up PURE so that it would delegate to its user when it is uncertain and thus is likely to make a mistake. Hence, ideally, when PURE delegates to its user, we would expect an improvement in the accuracy of the remaining items.

Table 4 shows the overall performance of PURE with respect to different percentages of delegated predictions. When we do not delegate any predictions, PURE obtains an accuracy of 89% (as was shown in Table 2). When we delegate only 25% of the most uncertain predictions, the results based on all performance metrics improve remarkably—for example, the accuracy, recall, and precision increase to 0.95. Similarly, when we delegate 75% of the most uncertain predictions, PURE achieves the highest performance of 0.99 in terms of all metrics. Thus, we observe that the delegated images are actually the ones that PURE would have made a mistake in.

An important question is whether the same upward trend holds for both private and public classes. Table 5 shows the performance of PURE for each class. For instance, when PURE does not delegate any predictions, it obtains an F1-score of 89% for both private and public classes.

Table 4. Overall Results for PURE at Prediction Delegation Rates (0%, 10%, 25%, 50%, and 75%) based on Uncertainty

Delegation %	Overall			
	Accuracy	F1	Precision	Recall
0	0.89	0.89	0.89	0.90
10	0.92	0.92	0.92	0.92
25	0.95	0.95	0.95	0.95
50	0.97	0.97	0.97	0.97
75	0.99	0.99	0.99	0.99

Table 5. Results for the Private and Public Classes of PURE at Various Prediction Delegation Rates (0%, 10%, 25%, 50%, and 75%) Based on Uncertainty

Delegation %	Private			Public		
	F1	Precision	Recall	F1	Precision	Recall
0	0.89	0.91	0.87	0.89	0.87	0.92
10	0.91	0.94	0.89	0.92	0.90	0.94
25	0.94	0.96	0.92	0.95	0.94	0.97
50	0.97	0.99	0.95	0.98	0.96	0.99
75	0.99	0.99	0.98	0.99	0.98	0.99

When PURE delegates only 25% of the most uncertain predictions, PURE improves F1-scores to 94% and 95% for the private and public classes, respectively. When it delegates 75% of the most uncertain predictions to its user, PURE yields the best performance with 0.99 F1-scores for both private and public classes, respectively. By increasing the number of the delegated predictions, the performance of the model can be improved for each class significantly.

Another dimension to understand the link between uncertainty and making errors is to analyze what fraction of wrong predictions fall under different uncertainty rates. Figures 6 and 7 present the uncertainty histogram for the failed and successful privacy prediction of PURE, separately for the private and public classes. The failed and successful predictions in the uncertainty ranges of each class are shown as a percentage among themselves. We observe that failed predictions have higher uncertainty in general, whereas successful predictions are more confident. This indicates that PURE is aware of its own ignorance and possible failures through its predictive uncertainty. When the most uncertain predictions are eliminated, its accuracy improve drastically.

Similarly, Figure 8 plots uncertainty against accuracy for PURE. The numbers on the particular points denote the ratio of test samples that are decided by PURE; the remaining samples are delegated back to the user because of the high uncertainty. The case when uncertainty is set to 1 is analogous, forcing PURE to make all of the privacy decisions, without delegating any case to the user. The accuracy of PURE at this stage is 89%. This is on par with the existing models in the literature that use the same dataset to predict privacy labels [40]. The more interesting cases are the ones where the uncertainty is high so that the PURE decides that there is too much uncertainty to answer and delegates them to the user. For example, for uncertainty threshold 0.4, 57% of the test samples can be decided by PURE, leading to an accuracy around 0.97. For uncertainty threshold 0.8, 69% of the test samples can be decided with PURE, leading to an accuracy around 0.95. This shows, as RQ1 asks, that PURE can capture the privacy ambiguity and can delegate such cases to its user.

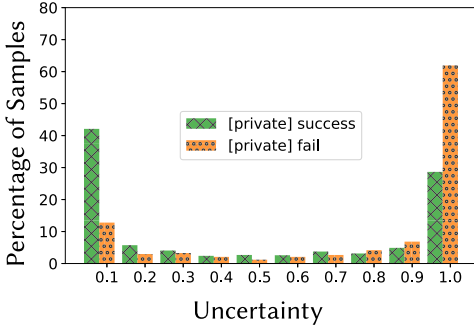


Fig. 6. Uncertainty distribution for the private category.

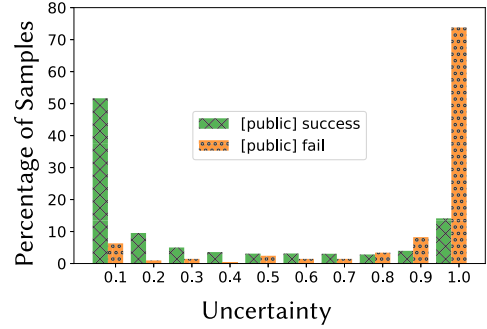


Fig. 7. Uncertainty distribution for the public category.

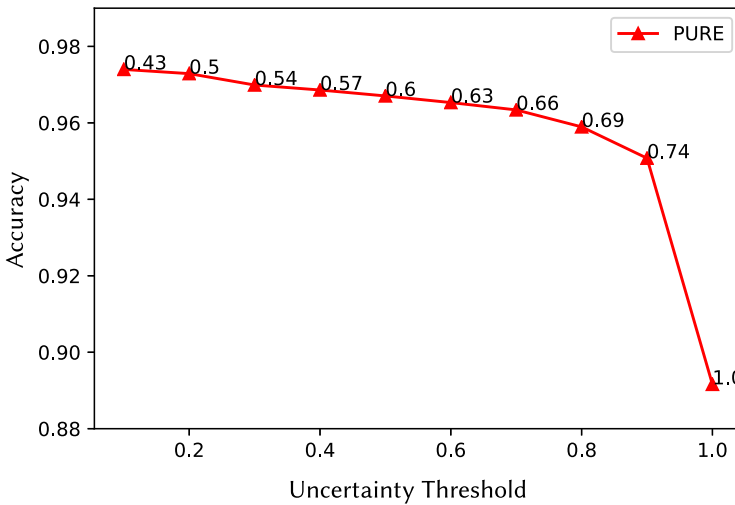


Fig. 8. The change of accuracy with respect to the uncertainty threshold.

*Comparison with alternative networks.* PURE calculates the uncertainty of its predictions and exploits it to refrain from making wrong privacy decisions for its users. To understand the effect of PURE in its calculations of uncertainty, we compare it to alternative predictive uncertainty models: MC Dropout [9] and Deep Ensemble [24], which depend on the class probabilities predicted by the neural network as well as a regular SNN. We implement SNN, MC Dropout, and Deep Ensemble with two softmax outputs using the same ResNet50 architecture with PURE. To measure the uncertainty of standard deep classifiers, entropy of their predictions has been used after normalizing it to have an uncertainty value between 0 and 1 [14, 31].

To have a meaningful comparison for uncertainty quantification, we use the normalized entropy as a proxy for the uncertainty for the PURE and SNN, MC Dropout, and Deep Ensemble models.

For PURE, we use the expected probabilities defined in Equation (2) to calculate the entropy. The entropy for the class probabilities  $p$  and  $(1 - p)$  is calculated as  $-[p \log p + (1 - p) \log(1 - p)]$ , then normalized by dividing to  $\log 2$ , which is the maximum entropy for the binary classification. Gal and Ghahramani [9] propose the MC Dropout method that represents model uncertainty using dropout in neural networks at test time. We add dropout layers after each of the non-linearities and

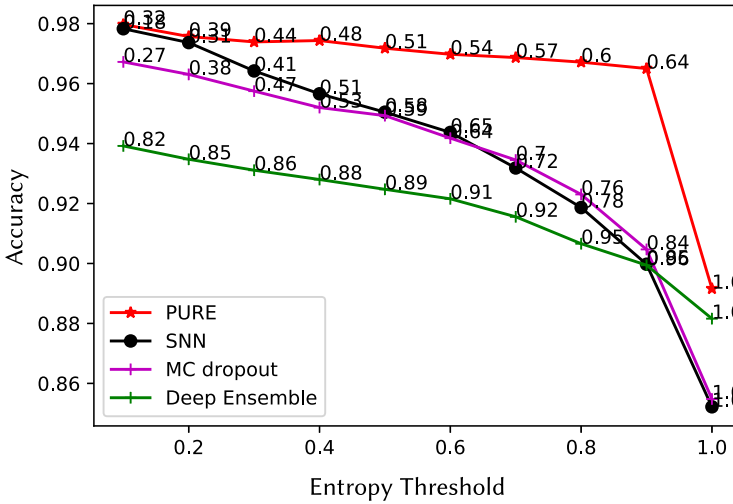


Fig. 9. The change of accuracy for different models with respect to different entropy thresholds.

set the dropout rate as 0.05.<sup>1</sup> We train a model, obtain the desired number of different predictions, and take the average of five predictions for each class. Lakshminarayanan et al. [24] propose an ensemble-based method called *Deep Ensemble* that quantifies predictive uncertainty. We use the Brier score (Equation (3)) as a proper scoring rule as the training criterion, train five models with the same architecture, and take the average of predictions.

Figure 9 demonstrates the variation of the test accuracy for the PURE, SNN, MC Dropout, and Deep Ensemble models as we change the thresholds for the normalized entropy for delegating predictions. PURE outperforms the SNN, MC Dropout, and Deep Ensemble models at almost all points. Its accuracy is higher than that of alternative models even when there are no delegated predictions and the disparity significantly increases as the predictions are filtered based on their entropy. When we select entropy threshold as 0.4, SNN achieves 95.6% accuracy using 51% of the data. For the same threshold, 53% of the data is used by MC Dropout, and the accuracy value is 95.2%. Deep Ensemble obtains an accuracy of 93% using 88% of the data, whereas PURE achieves 97.8% of accuracy for 48% of the predictions at the same threshold. Our observation is consistent with the literature, where the DNNs are criticized as being overconfident, hence misleading, when they make mistakes [14]. One important aspect to note here is the distribution of the data over various entropy thresholds. In principle, we want to use the entropy threshold to decide if a decision will be delegated to the user. Consider PURE in Figure 9. When entropy is 0.1, PURE will only classify 32% of the data and delegate the remaining to the user. Although this is a large percentage to delegate, it comes with the advantage of 98% accuracy. If PURE sets its entropy to 0.8, then it will classify 60% of the data and still yield an accuracy of 98%. When it chooses to classify all of the data, then the accuracy will drop to 89%. Contrast this ability to configure based on entropy to Deep Ensemble. With Deep Ensemble, even when the entropy is set to 0.1, the personal assistant will classify 82% of the data itself, with low flexibility in delegating the choices to the user. Next, we study the accuracy changes of these models based on their data usage.

Figure 10 plots how the F1-score changes for the *public* and *private* classes when the PURE, SNN, MC Dropout, and Deep Ensemble models delegate certain percentages of their most uncertain

<sup>1</sup>0.05 yields the best performance among {0.01, 0.1, 0.25, 0.5}.



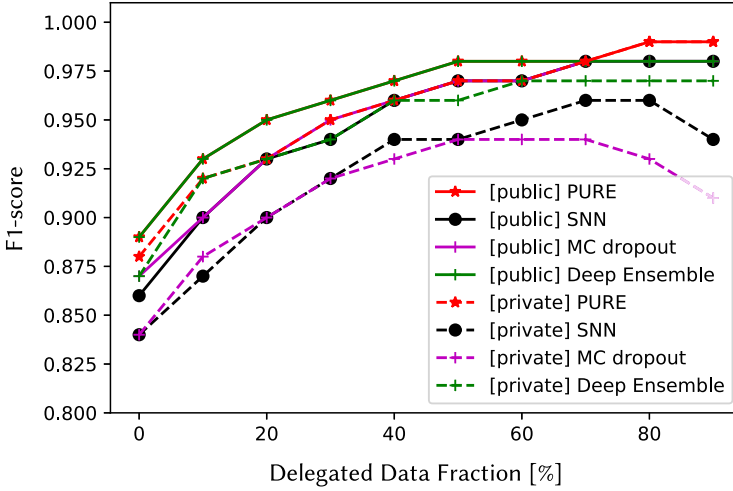


Fig. 10. F1-scores for the private and public classes relative to the percentage of delegated decisions.

predictions based on the entropy. The F1-scores of PURE and Deep Ensemble models are better than SNN and MC Dropout for each class, and the gap is bigger for the private class. PURE outperforms Deep Ensemble for both classes when the rate is higher than 0.7. The F1-score of PURE improves further and reaches 0.99 for both private and public classes. However, the F1-score of the private class for SNN and MC Dropout decreases when the most uncertain 80% of the data is neglected and the remaining most certain 20% is used for the calculation of the F1-score. The decrease in the F1-score for the private class in Figure 10 indicates that SNN and MC Dropout are overconfident, whereas PURE can exploit its well-measured uncertainty to avoid wrong privacy decisions. With randomization tests [30], we can show that the improvements of PURE over existing models is statistically significant ( $p$ -value  $< 0.05$ ). We answer RQ2 positively such that PURE outperforms SNN, MC Dropout, and Deep Ensemble by expressing uncertainty better.

*Personalized misclassification risk.* Each user may have a significantly different cost for the misclassification of the private content. In this section, we demonstrate the flexibility of PURE for adapting users' perceived risk of such mistakes and its ability to avoid them by refraining from making privacy decisions when uncertain.

For this purpose, we consider five broad categories of personas, *non-sensitive*, *semi-sensitive*, and *sensitive*, which have a different risk matrix  $R$ . The non-sensitive user has the same perception of risk for the misclassification of private and public image (i.e.,  $R_{01} = R_{10} = 1$ ). This means that, for the non-sensitive user, the KL term in the loss of the PURE does not weigh the evidence for private and public categories differently. However, for the semi-sensitive users, misclassifying private image as the public is a few times more unacceptable (i.e.,  $R_{01} = 1$  and  $R_{10} = \{3, 5, 7\}$ ). We also have the sensitive user in which misclassifying a private image as public is 10 times more unacceptable for such a user (i.e.,  $R_{01} = 1$  and  $R_{10} = 10$ ). This means that PURE is significantly more penalized for making a wrong prediction in the private class.

Table 6 shows our results. For the non-sensitive persona, the results are as before. For the sensitive persona, the recall for the private category improves significantly at a cost of having lower recall for the public category. In other words, PURE prefers to classify a content as private over public when in doubt. This behavior increases the number of predictions for the private category for the sensitive user (i.e., private recall increase from 0.86 to 0.91). While doing so, it does not sacrifice its overall recall and the accuracy. Our results indicate that by increasing  $R_{10}$ , we increase

Table 6. Results for Five Different Risk Personas

Persona	Non-Sensitive	Semi-Sensitive			Sensitive
Risk Values	$R_{01} = 1$ $R_{10} = 1$	$R_{01} = 1$ $R_{10} = 3$	$R_{01} = 1$ $R_{10} = 5$	$R_{01} = 1$ $R_{10} = 7$	$R_{01} = 1$ $R_{10} = 10$
[Overall] Accuracy	0.89	0.89	0.90	0.90	0.90
[Overall] Recall	0.89	0.89	0.90	0.90	0.90
[Private] Recall	0.86	0.87	0.89	0.90	0.91
[Public] Recall	0.92	0.91	0.90	0.89	0.89

Table 7. Ratios of Prediction Whose Uncertainty Values Are Greater Than 0.7 ( $\theta$ )

	Round I	Round II—Personal	Round II—Random
User 1	0.32	0.19	0.34
User 2	0.30	0.21	0.27
User 3	0.34	0.22	0.29

private recall and thus classify more images as private; as a result, we obtain a lower recall for public images. Notice that the  $R$  value belongs to a user and can be adjusted as needed.

*Data personalization.* PURE delegates a decision to its user when it is uncertain about a prediction. Ideally, we would like to minimize the number of times this happens while keeping the accuracy high. The personalization is meant to serve this purpose. To see if this is indeed achieved, we need to perform a comparative analysis where in the first round no personal data is used and in the second round the personal data is added. To realize this, we select three users who have annotated the most images, as each annotator has annotated different numbers of images:

- *Round I:* Train a model without using personal data.
- *Round II—Personal:* Tune a trained model in Round I using personal data annotated by a user.
- *Round II—Random:* Tune a trained model in Round I using data annotated by others.

Figure 11 shows the change of samples (%) in which PURE prefers to delegate the decision of labels to the user. We observe that PURE delegates less to its user when it makes use of the personalization module.

A closer look in Table 7 shows the ratio of samples at each round when the uncertainty threshold is 0.7. These samples belong to the top three users who annotate the most images. For instance, for the first user, PURE delegates 32% and 34% of test samples after Round I and Round II—Random, respectively. However, only 19% of uncertain cases can be delegated to the user when we tune the trained model with personal data at Round II. In light of these results, we answer RQ3 positively: PURE can adjust its behavior based on the personal risk and expectations of its user, as well as help the user deal with fewer decisions.

An interesting aspect to note is that the number of images used to personalize can affect the behavior of the data personalization approach. Given the limited number of annotators with a pre-defined set of images, we currently cannot study such questions, but it would be useful to provide bounds to guide users to personalize the assistant even further.

## 6 CONCLUSION

This article proposes a personal privacy assistant, PURE, that helps its user make privacy decisions by recommending privacy labels (private or public) for given contents. PURE is uncertainty-aware

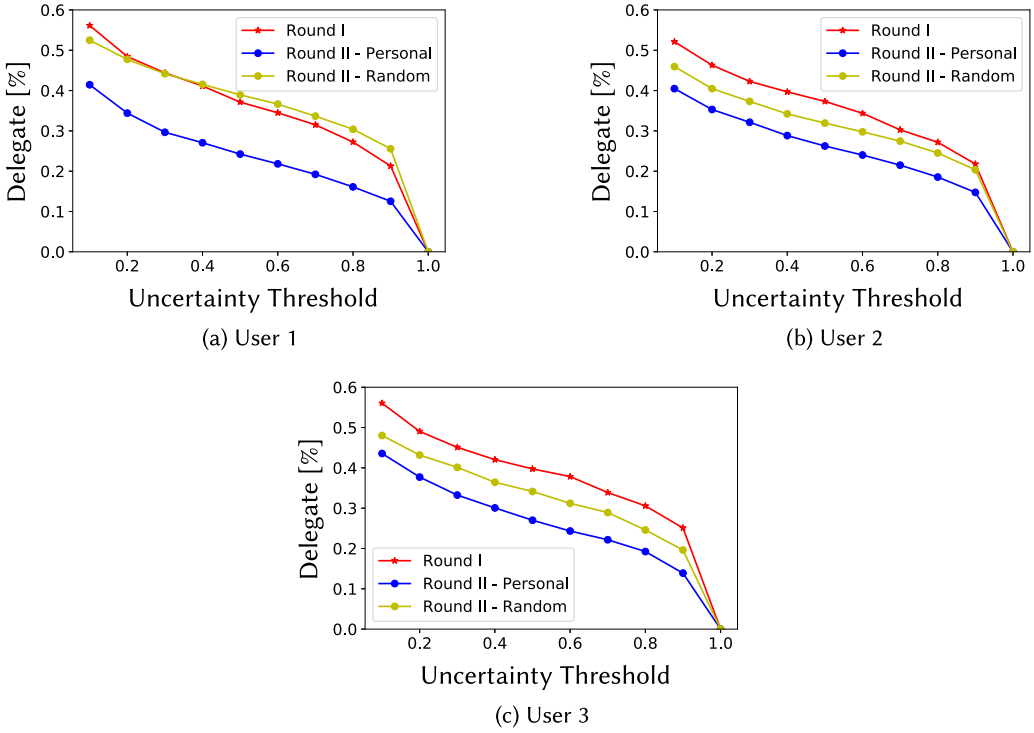


Fig. 11. The change of delegated samples for each round with respect to different uncertainty thresholds.

in that it captures the privacy ambiguity using uncertainty modeling and delegates decisions for ambiguous cases to its user. PURE is personalized in that it is capable of making a privacy decision by incorporating the user’s risk of misclassification and using personally labeled data. Through its personalization, PURE is also unobtrusive, as it does not consult its user only when it is uncertain. Our experimental results show that PURE obtains a high accuracy without even consulting its user at all. Our comparison with other models in the literature shows that PURE captures uncertainty well and that most of the content it identifies as uncertain is the content with which it would have made an error if it were to classify the content itself. Thus, the overall accuracy of PURE steadily increases as it delegates uncertain cases to its user. Moreover, our results show that PURE can indeed adjust its behavior based on the personal risk and expectations of its user and is able to decrease the delegations to its user by fine-tuning using personal data.

This article opens up interesting directions for future research. Currently, we start with an uncertainty-aware model for privacy classification and enhance it further with users’ personalized risk for misclassification. An interesting direction for further research is to enable PURE to have deeper interactions with the user. For example, it could interact with the user to obtain labels for the images that it is uncertain about and further enhance its ability for classification with this new personal data. Similarly, it could attempt to explain the uncertainty to its user so that the user can help in guiding PURE in the right direction. Semantic information about the content, such as tags, could aid in the explanation. Another important direction is to enable interaction between different personal assistants to help create a collaborative environment for preserving privacy. Currently, we assume that the content a personal assistant decides on belongs to its user alone. However, many times, content such as group images or co-edited documents might belong

to more than one user [42]. Extending PURE to act collaboratively in such settings would be useful. Finally, a user's privacy preferences are many times relational. In other words, a user might be fine with sharing content with a friend but not with a colleague. Our current approach does not capture with whom the content is shared. It would be interesting to learn relation-based sharing behavior of users. Another interesting direction would be to investigate how PURE can learn when to delegate its decisions to the user. Currently, PURE has a preset threshold value  $\theta$  by capturing user involvement such that it makes a decision when a prediction's uncertainty value is below  $\theta$  and delegates the decision otherwise. It would be useful if PURE could automatically adjust  $\theta$  based on user feedback.

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Received 22 April 2022; revised 12 August 2022; accepted 29 August 2022