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Leveraging Deep Learning for Automated Image Anonymization in the Insurance Domain

SINTESI

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Sommario

Questo lavoro di tesi è il risultato di uno stage della durata di cinque mesi, inserito all'interno del programma *Junior Consulting* promosso da ELIS Consulting & Labs. Durante questo periodo, la candidata ha preso parte ad un progetto di consulenza finalizzato all'utilizzo degli strumenti di Image Analytics per la corretta gestione dei dati sensibili che vengono processati in ambito assicurativo, in conformità con la normativa Europea GDPR. L'obiettivo del progetto è stato quello di realizzare un algoritmo di *Object Detection* ed anonimizzazione di persone, targhe e numeri di telaio presenti in immagini, basato sui concetti di apprendimento supervisionato delle reti neurali profonde. La componente tecnologica dell'algoritmo è stata prodotta utilizzando il *framework* TensorFlow, che ha consentito di implementare una versione del modello RetinaNet in linea con le specifiche del *task* di anonimizzazione che è stato richiesto dal committente di progetto. Il lavoro svolto durante l'attività progettuale ha fornito lo spunto per lo svolgimento di una ulteriore analisi. L'oggetto dell'indagine ha riguardato le possibili modalità di sfruttamento dei più recenti strumenti di Intelligenza Artificiale nei processi dell'industria assicurativa, in modo tale da supportare una strategia di trasformazione digitale che dipende largamente dalla corretta gestione ed interpretazione dei dati. I risultati ottenuti dall'analisi della letteratura in merito evidenziano come l'implementazione di strumenti basati su modelli di *Machine Learning* e *Deep Learning* possa consentire alle aziende del settore assicurativo di migliorare i processi basati sull'analisi di dati strutturati e non strutturati (come le immagini). Tale miglioramento è potenzialmente quantificabile mediante l'incremento delle metriche di performance legate alla soddisfazione del cliente nel medio/lungo termine.

Abstract

This thesis work is the result of a five-month internship, included in a talent-program called *Junior Consulting*, promoted by ELIS Consulting & Labs, in Rome. During this period, the candidate took part in a consulting project aimed at using Image Analytics tools for the proper management of sensitive data which are usually processed in insurance companies' business processes, in order to be compliant with the GDPR European regulation. In this respect, the need has emerged for the implementation of an *Object Detection* algorithm, also aimed to remove *license plates*, *Vehicle Identification Numbers* (*VIN*), and *persons shape* from images used for insurance purposes, by relying on the supervised learning of deep neural networks. The technological part was realized using the TensorFlow framework, which allowed to implement a customized RetinaNet model in line with the anonymization task requirements that were specifically sought by the project client. In addition, the work carried out during the project provided the basis for further context analysis. The object of this additional survey concerns the possible ways of leveraging the most recent Artificial Intelligence tools in insurance business processes, in order to support a digital transformation strategy focused on value deriving from meaningful interpretation and management of data. The results which were obtained from the literature review shows how the implementation of *Machine Learning-based* and *Deep Learning-based* tools allow insurance companies to improve their data-driven processes, unlocking value from the analysis of both structured and unstructured data (e.g., images). The benefits of this approach are expected to be measured in the medium/long run, in terms of positive impact on the customer satisfaction key performance indicators in the insurance domain.

1. Context Analysis

Digitalization can be defined as the integration of the analogue and digital worlds with new technologies that enhance customer interaction, data availability and business processes. This phenomenon is affecting a multitude of industrial fields across the board, and the insurance industry has not been left out of this scenario. In fact, insurance is witnessing a shift from a value proposition based on the concepts of *detect and repair* to that of *predict and prevent*. This change in the strategic vision is currently made possible by the emergence of new technological solutions based on the principles of Artificial Intelligence (e.g., deep learning algorithms), which can impact the insurance industry along three main broad categories of change (Eling & Lehman, 2017): (i) the way insurers and customers interact; (ii) automatization, standardization and improvement of business processes' effectiveness and efficiency; (iii) opportunity to modify existing products. The most emblematic business cases that have been identified from the literature analysis concern the application of technologies in the processes of the insurance industry value chain, such as: Product Development, Claims Management, and Underwriting. Specifically, the case study in this thesis referred to the application in the Claims Management process. However, in order to unlock the potential of these tools in the business processes, the main players in the insurance domain have to structure their strategy on the basis of these four main drivers, as stated in McKinsey report (2018): (1) Data capabilities; (2) Organization and talents; (3) Change management; (4) Models and tools management.

Specifically, to point (1), the proper management and interpretation of the information provided by big data is an activity that has become critical in this industry domain. If insurance companies want to ensure a strategic and competitive positioning in the market that guarantees sustainable success in the medium/long term, they have to analyze and understand which Artificial Intelligent-based techniques are most appropriate to extract valuable knowledge from their input data. Furthermore, concrete use cases for the final customer have to be identified. In fact, insurance companies daily process a large amount of both structured and unstructured data (e.g.: road accidents or open-claims related images). This data needs to be constantly organized and used in ways that support the high-level management decision-making process and generate new analytics insights. The current challenge is to process and transform raw data into meaningful, high-quality data at a reasonable cost. The company that commissioned the project is actually implementing a strategy in line with the principles described above. To do this, it has established a dedicate Analytics Solution Centre, aimed the carry out activities that are intended to support the digital transformation of the other Business Units of the company group. The main goal is to exploit the value of new tools and technologies to boost process automation in multiple business domains.

2. Anonymization for car image: project's overview

Anonymization for car image was born as a consulting project, within the Consulting & Labs division of CONSEL (*CONSORZIO ELIS per la formazione professionale superiore*). CONSEL is a non-profit consortium of small, medium and large enterprises. The project's client (and Sponsor) is a member of CONSEL consortium, and it is represented by one of the largest insurance operators both in Italy and Central

Europe. The commissioned project inserts itself in a wider strategic view, concerning the promotion and the support of *Data analytics* tools in the insurance value chain. The potential of *Machine Learning* and *Deep Learning* techniques have been identified by the project's client. Nevertheless, unleashing the value of advanced analytics with these instruments in such a domain requires compliance with the most recent European regulation on sensible data protection, the *General Data Protection Regulation* (GDPR), mostly for privacy reasons. In this respect, the need has emerged from the blurring/removal of persons, license plates and Vehicle Identification Number (VIN) from the photographic material and footage owned by the client and used for insurance purposes. This can be achieved by the design, training, and validation of an *Object Detection* algorithm based on deep convolutional networks, capable of first adding a bounding box around a specific object located in the image, and then, blurring such part. The algorithm in question has been trained ad-hoc in order to autonomously perform the specific *Object Detection* task required by the client. The training phase was based on deep convolutional networks' *supervised learning* concepts. The algorithmic model was exercised by feeding it with an image dataset provided by the client itself, consisting of photographs related to claim practices.

To reach the project's goal, ELIS team scheduled the main project activities by grouping them into three main phases: *Preliminary Steps, Training and Validation,* and *Final Results.* The list of project's sub-phases which were carried out in each phase, as well as the methodologies used and the outputs produced, are illustrated in *Table 1.*

PRELIMINARY STEPS PHASE					
Sub-phase	***Activities***	***Methodological steps***	***Output(s)***	***Role***	***§.***
Environment Setup	- Definition of HW and SW requirements - VPN setup and connectivity validation - VM setup and dataset access - Annotation tools access	- Establishment of a procedure for the access to VM via VPN connection - Establishment of a data visualization procedure via the VM - Establishment of annotation tools access procedure via the VM	*Sprint 1* Deliverable documentation	C	4.1
Data Preparation and Functional Architecture Analysis	- State-of-the-art analysis - Benchmarking of Object Detection algorithms - Dataset preliminary analysis - Person Detection Test based on pre-trained RetinaNet - Dataset preparation (Annotations) and definition of the Analytical Base Table (ABT) - First Annotation Round on the real dataset (FAR) - Definition of Business KPIs	- Collection and analysis of scientific literature in accordance with the project's scope - Sample analysis on real dataset - YOLOv2 and RetinaNet demos implementation - Establishment of RetinaNet Installation procedure on the VM - RetinaNet person detection implementation on real dataset - Establishment of Annotations procedure	*Sprint 2* Deliverable documentation *Sprint 3* Deliverable documentation	R, C	4.2

TRAINING AND VALIDATION PHASE					
Sub-phase	***Activities***	***Methodological steps***	***Output(s)***	***Role***	***§***
Training and Validation of the Object Detection Algorithm (Iteration 1, Iteration 2, Iteration 3)	- RetinaNet ImageNet-based implementation for License Plate & VIN detection - RetinaNet COCO-based implementation for License Plate & VIN & person detection - Second Annotation Round on real dataset (SAR) - Definition of the functional architecture - Definition of the Final Model - Fine-Tuning of the Final Model - Third Annotation Round on real dataset (TAR) - Final Dataset Definition - Preparation of the Final ABT - Final Training Iteration - Validation of the Final Training Iteration - Test of the Final Training Iteration	- Establishment of model Initialization procedure - Establishment of model Training procedure - Establishment of model Validation procedure - Establishment of model Conversion procedure - Establishment of model Implementation procedure - Definition of models' comparison criteria (Business KPIs) - Models performance comparison on Person detection - Models performance comparison on Person & License Plate & VIN detection - Final Dataset analysis	*Sprint 4* Deliverable documentation *Sprint 5* Deliverable documentation *Sprint 6* Deliverable documentation	R, C	5.2
FINAL RESULTS PHASE					
Sub-phase(s)	***Activities***	***Methodological steps***	***Output(s)***	***Role***	***§***
Blurring/ Removal of detected objects and Final Tests	- Fine-Tuning of the Final Model - Implementation of the Algorithm for Blurring/Removing the Detected Objects - Test of the Algorithm for Blurring/Removing the Detected Objects	- Establishment of the Blurring Function procedure - Integration between Model Implementation and Blurring Function procedure	*Sprint 6* Deliverable documentation *Sprint 7* Deliverable documentation	C	6.1, 6.2
Complete algorithm for Anonymization	- Implementation of the Complete Algorithm for Anonymization - Validation of the Complete Algorithm for Anonymization - Presentation of the Final Results	- Establishment of the Final Model Implementation procedure	*Sprint 8* Deliverable documentation	R, C	6.2

Table 1: Project's Phases, sub-phases, and methodological steps.

3. Preliminary steps

3.1 Environment Setup

The main objective of this first project phase was to define, together with the project client, all the technical requirements (i.e., hardware and software) of the needed resources, in order to set up the proper development setup for the algorithmic solution.

3.1.1 Results

The two project's interested parties stipulated that the project work would have been carried in a remote way, from ELIS headquarters in Rome, comprising daily check-in and periodical meetings with the client's side. Firstly, a Virtual Private Network (VPN) was set up, in order to access corporate applications and software resources, enabling the efficient sharing of the data. Secondly, a *Data Science Virtual Machine* (VM) was provided by the client. The training of algorithmic models based on deep neural networks is very expensive from a computational point of view. For these reasons, a VM including readily available GPU clusters with pre-configured deep learning tools was selected.

3.2 Data Preparation and Functional Architectures Analysis

In collaboration with the client, it was developed a proper approach to solve the *Object Detection* task (i.e., the recognition of instances belonging to a predefined set of object classes and the description of the location of each object detected in the image using a drawn rectangle) on specific object classes (*license plate*, *VIN*, and *person shape*) within the images owned by the client itself.

In this respect, the second project phase had several goals:

- Carry out a scientific literature analysis on the existing algorithmic models, easily-implemented from the technological point of view and aimed to perform the *Object Detection* of sensible data;
- Understand which architectural model was most suitable to meet the specific *Object Detection* task required by the client, from the algorithmic design point of view. This goal was achieved by realizing a benchmarking between two different architectures: YOLOv2 and RetinaNet;
- Define the key performance indicators for measuring and evaluating the model's performances from a *business* point of view (i.e., capable of measuring both the model accuracy and the compliance with the project's main goal of detecting sensitive data).

3.2.1 Results

With respect to the project scope and objectives, the state-of-the-art analysis has identified RetinaNet to be the most promising *Object Detection* algorithm, and TensorFlow as the underlying *framework*. Specifically, `keras-retinanet` implementation of RetinaNet architecture (developed by *Fizyr*[1]) was selected as the referenced open-source software.

RetinaNet resulted to be the most promising architecture in terms of speed/accuracy trade-off. This choice was also made given the results of the literature review and in conjunction with several tests that were executed by the team in order to verify the functionality of various *Object Detection* models. Furthermore, the preliminary sample analysis performed on the client's images stored in the VM showed a distribution of the object classes within the images which was consistent with the optimal conditions for the applicability and the exploitation of RetinaNet's *Object Detection* functions.

[1] https://github.com/fizyr/keras-retinanet

In order to optimally train the neural network to perform the detection of *person shape* AND/OR *license plate* AND VIN, it was necessary to develop and validate a series of structured procedures, to be iterated for each following model training and validation steps. In particular, in this project's phase, the Annotations procedure was defined. Annotations[2] are fundamental in order to proper feeding the neural network with the images containing real localization and class for each object of interest appearing in them. As far as the key performance indicators were concerned:

- *Average Recall* value was decided to be more interesting *business* KPI for evaluating the performance of a single model. It indicates how many of the objects of interest (*license plate, VIN*, *person shape*) the algorithm is able to "catch", compared to those that are actually present in the image. The target value requested by the project client was at least to 80% for the Final Model;
- *Average Intersection over Union* (*IoU*) was decided to be considered the second *business* KPI. It indicates the overlap between the detected bounding box and the real bounding box which contain the sensitive data that must be recognized. The target value requested by the project client was at least to 70% for the Final Model;
- *mAP* (i.e., *mean Average Precision*) was chosen as the reference metric for comparing the performances between different models. It indicates the mean of the *Average Precision* values, evaluated on the detection of each class. The target value requested by the project client was at least to 70% for the Final Model.

4. Training and Validation

4.1 Definition of the Functional Architecture

Once the most appropriate architecture was determined from the algorithmic point of view, the main objective of this project phase was to define the final solution from a functional point of view. In these terms, it was intended to define whether the macro-task of detecting the three classes should be eventually split into two sub-tasks, to be performed by separate components in the system. In this respect, several steps were followed by the project team in order to determine the best choice between:

(i) A linear "pipeline", implementing a single, multi-class detector for *person shape* AND VIN AND *license plate* simultaneous detection, and then blurring such parts, as shown in *Figure 1*;

(ii) A split "pipeline", consisting of two separate detectors operating in parallel, the former for *person shape* detection only and the latter for *license plates* AND VIN detection. This approach is exposed in *Figure 2*.

[2] Annotations (or Grund Truth) consists of both real localization coordinates and class of the objects to be detected. This information is directly provided on the images that are going to make up the training dataset of the neural network. This set is fed into the algorithm in order to teach to the network the "features" that characterize every class iteratively.

To achieve this goal, a specific test was carried out with regard to the detection of *person shape* class only, comparing the performance of the RetinaNet-based inference model (i.e., not ad-hoc trained) used in the *Data Preparation and Functional Architecture Analysis* project phase (see *Sprint 3 Inference Model* in Figure 3) with other two RetinaNet-based trained models on the simultaneous detection of all three classes (see both *Sprint 4* Trained Model and *Sprint 5* Trained Model in *Figure 3*). This step, belonging to the decision-making process reported in *Figure 3*, is illustrated in the first block of the flowchart.

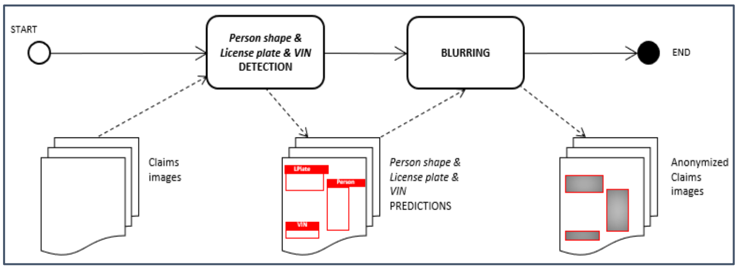


Figure 1: Functional Architecture Solution (i)

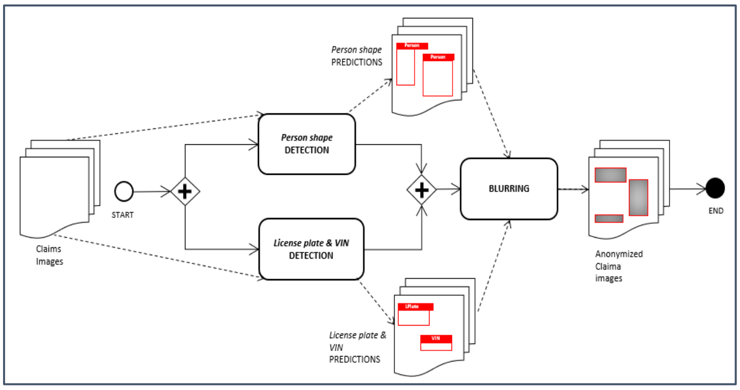


Figure 2: Functional Architecture Solution (ii)

4.2 Training and Validation of the *Object Detection* Algorithm

This project Sub-phase has been further divided into three iterations, and for each of them different tests have been carried out for the RetinaNet model. Several model configurations have been tried. The aim was to understand, once the functional architecture was defined, which was the optimal setup of the model parameters and hyperparameters, as well as the final division of the dataset so as to obtain *Average Recall* and *Intersection over Union* values that fit the client's requirements. The decision-making process, as well as the activities carried out by the project team to achieve these objectives, were modeled in the flow diagram of *Figure 4*.

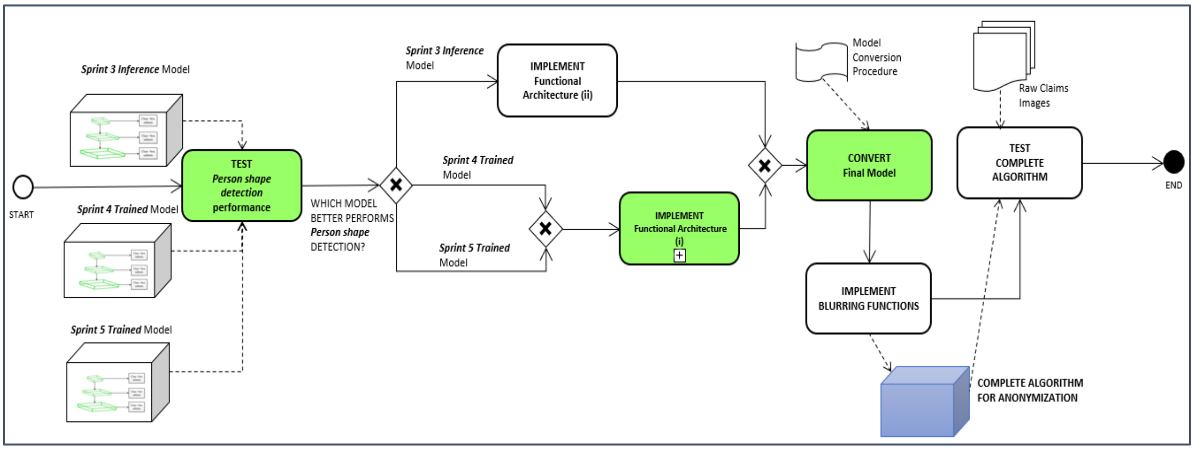


Figure 3: Decision flow diagram regarding the steps carried out by the project team during Training and Validation of the Object Detetction algorithm project phase. In green, it is highlighted the effective decision-making process followed by the project

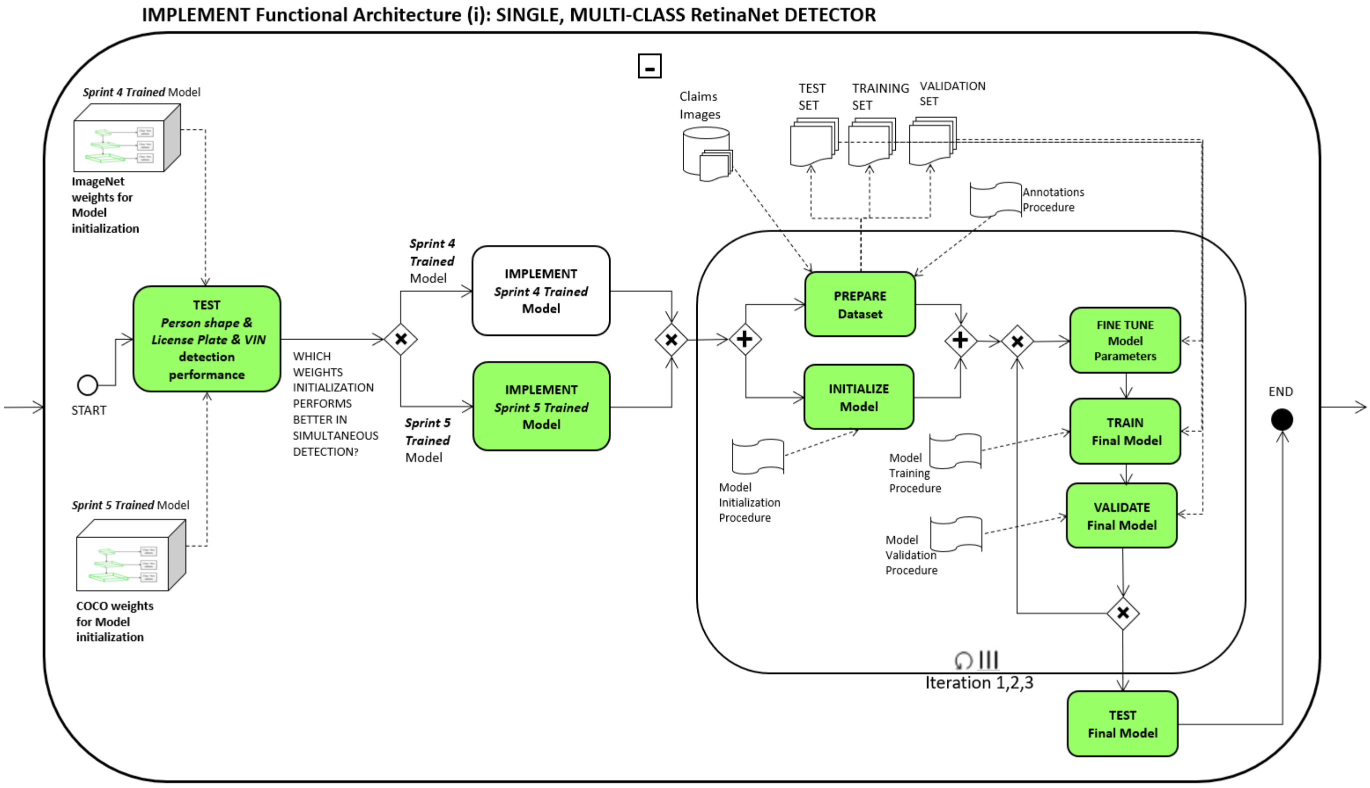


Figure 4: Flow diagram related to the explosion of the activities that were carried out by the project team in order to implement the Final algorithmic solution with Functional Architecture (i)

4.2.1 Results

During this project phase, the procedures of model Initialization, Training, and Validation have been structured and defined. As far as the functional architecture was concerned, an "end-to-end" solution was chosen, which performs simultaneous detection of the three object classes, as shown in *Figure 1*.

The Final *Object Detection* Model, which was validated during *Sprint 7*, was decided to be with the following setup:

- RetinaNet Keras-based implementation, with ResNet50 backbone for performing *feature extraction*
- Model initialization through *Transfer Learning* approach (COCO-dataset weights initialization)
- No Negative Examples (i.e., images that do not contain any of the objects of interest) included in the final training set
- Customized input parameters (specifically: customized *Anchor* parameters), in order to better fit the objects of interest's shape

Furthermore:

- The total number of images provided by the project client was recorded to be 13893, 6479 (46,6%) of them containing at least one object of interest (*license plate* OR *VIN* OR *person shape*)
- During Iteration 3 of the *Training and Validation phase*, the 6479 images have been randomly shuffled and divided into Final Training Set (70%*6479 = 4535 images), Final Validation Set (25%*6479 = 1649 images), and Final Test Set (5%*6479=324 images)
- During Iteration 3, the Final Model was trained with 4535 images
- The Final Model training phase performed during Iteration 3 took 4 working days to be completed

- The Final Model was validated over 1619 images, from which final *Average Recall*, *Average IoU*, and *mAP* have been computed.
- The *Average Recall* performed by Final Model resulted to be 92,61% (as shown in *Table 2*)
- The *Average IoU* performed by the Final Model resulted to be 77% (as shown in *Table 2*)
- The *mAP* performed by the Final Model resulted to be 82% (as shown in *Table 2*)

Object Class	***Object instances***	***Detected***	***Missed***	***IoU***	***Recall***
License Plate	1203	995	208	82%	89,76%
Person	836	603	233	71,87%	88,67%
VIN	236	225	11	76,15%	99,40%
Final Model *mAP* **82,09%**				*Average IoU* **77%**	*Average Recall* **92,61%**

Table 2: Final Model Performances Summary

5. Final Results

5.1 Blurring/Removal of the detected objects and Complete Algorithm for Anonymization

The activities carried out in this last project phase consisted of the implementation of blurring functions, and the release of the Complete Algorithm for Anonymization (as it can be seen in *Figure 3*). The output of the Final Model subsists in both class label and bounding box's coordinates for each detected object in the images fed as inputs. Once identified and localized the region containing sensible data, the last part of the algorithm has to anonymize that region in such a way that the resulting image cannot be used in the original form. In order to achieve this goal, the project team relied on OpenCV tool. OpenCV is an open-source Python library currently used to perform image modification operations, and it was leveraged in order to achieve the desired anonymization result.

Once the anonymization functionalities have been integrated together with the *Object Detection* ones provided by the implementation of the Final RetinaNet-based Model, the Complete Algorithm was further tested on a new sample of images provided by the client, in order to verify the proper run of the desired functions, as well as the algorithm's robustness from the key business performance metrics point of view.

5.1.1 Blurring Results

Two specific OpenCV functions were implemented to operationally obtain the removal of the recognized objects: `rectangle` and `blur`. The first one is fed with the predicted bounding boxes coordinates in order to highlight the region in which the *Object Detection* model founded sensible data. The blurring function applies a kernel (i.e., a small matrix) over the image in order to obtain the blur effect. The kernel dimension was set in function of the image's size, achieving in such a way the same kind of blurring effect, independently from the input image resolution. Specifically, it was used:

$$k = \frac{1}{15} * image\ width$$

In *Figure 5* below, it is shown an example of an image, before and after feeding the Complete Algorithm for anonymization, constituting the project's final deliverable output.

Figure 5: An example of applying the Complete Algorithm for anonymization to an input image (on the left side) containing two of the classes of interest: *license plate* & *person shape*, respectively.

6. Conclusions

In this thesis work, the car images anonymization task in the insurance domain has been addressed. In order to do this, a *Deep Learning*-based framework has been proposed as the proper solution by the project team. In conclusion, it can be reasonably assumed that using *Deep Learning*-based tools has the potential to enable insurance companies to create value by improving their data-driven business processes, in line with the current digital transformation, and maintaining a customer-centric approach. Looking forward, the research aims to extend the actual performances achievable by *Deep Learning* models used to solve *Object Detection* tasks. As far as other applications are concerned in this field, video anonymization, as well as vehicles damages recognition/classification, actually represents arguments for further studies.

I contenuti del lavoro svolto hanno fornito la base per la stesura di un articolo scientifico*, che è stato accettato per la presentazione alla *R&D Management Conference* 2019 di Parigi, nella *Track 1.3: Data Science for Innovation Challenges.* L'articolo tratta dell'impatto che il *deep learning* e le tecniche di *advanced analytics* hanno su una azienda del settore assicurativo in termini di incremento della sua capacità di innovare.
Riferimenti al progetto si trovano anche nell'articolo pubblicato su ZeroUno "*L'innovazione del Gruppo Generali incontra i Big Data e l'AI*"**

*ANDREOZZI A., RICCARDI CELSI L., MARTINI A. (2019), "*Leveraging Deep Learning for Image Anonymization in the Insurance Domain*", special track on Data science for innovation, R&D Management Conference, Paris, 17-21 June.

**TODOROVICH P. (2019), "*L'innovazione del Gruppo Generali incontra i Big Data e l'AI*", ZeroUno, 18 marzo, https://www.zerounoweb.it/analytics/big-data/linnovazione-del-gruppo-generali-incontra-i-big-data-e-lai/

Appendix A. Training and Validation of the *Object Detection* Algorithmic Model

The main purpose of this Appendix is to provide further insight into the *Object Detection* model training and validation phases, by using illustrative figures of the two processes.

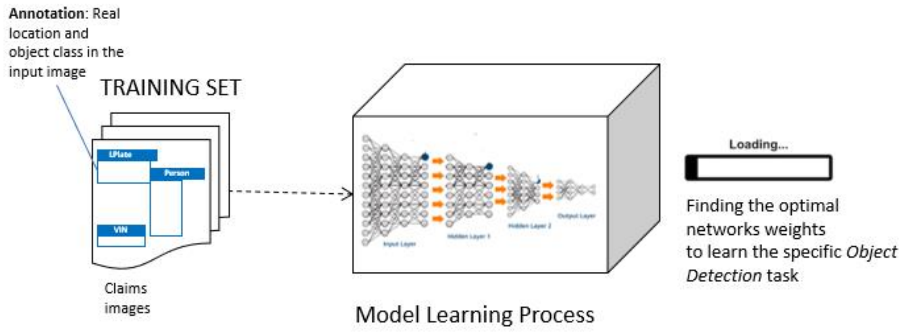


Figure 6: Model training phase

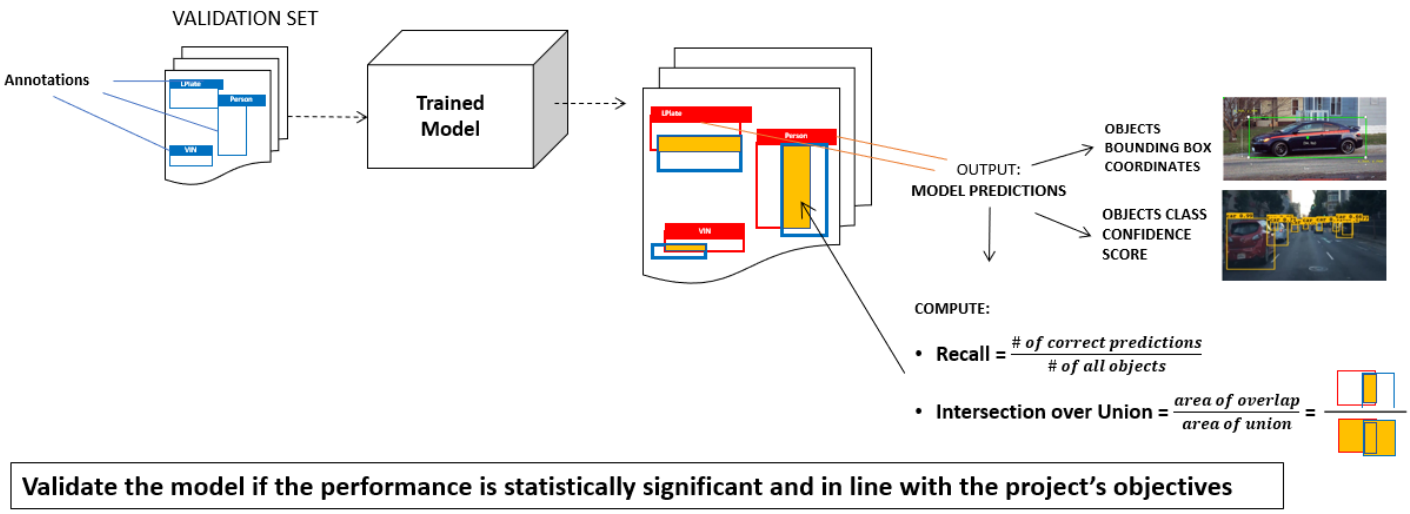


Figure 7: Model validation phase

Appendix B. Image Anonymizer Visual App

The second part of *Anonymization for car image* project was aimed at developing a web app, accessible via any web browser, embedding the required anonymization functions for the visual analytics and image categorization purposes. The web app consists mainly in a user-friendly interface where the pictures can be uploaded and the result (i.e., the output of the Complete Algorithm for anonymization) produced can be visualized. It comes that this interface represents the tool through which the user can take advantage of the automated anonymization process provided by the Complete Algorithm. The Visual App was designed and produced by an additional resource of ELIS Consulting & Labs, that coordinated the work with the project team during the whole the development phase.

The use of this application is intended for the company's employees (e.g., insurance assessors, technical experts), who have to collect customers' images related to road accidents or various types of claims. The images that are collected during Claims Management process have often to be processed and/or sent to other operators in the value chain, and to do this the data has to be anonymized at the lowest cost in terms of time, in order to support the user in carrying out the practices to advance in the Claim Settlement process. The visual app represents the concrete output of *Anonymization for car images* project, and it is going to be integrated with other data analytics tools in the R&D division of the company. In *Figure 6* below, the graphical template of the visual App is shown.

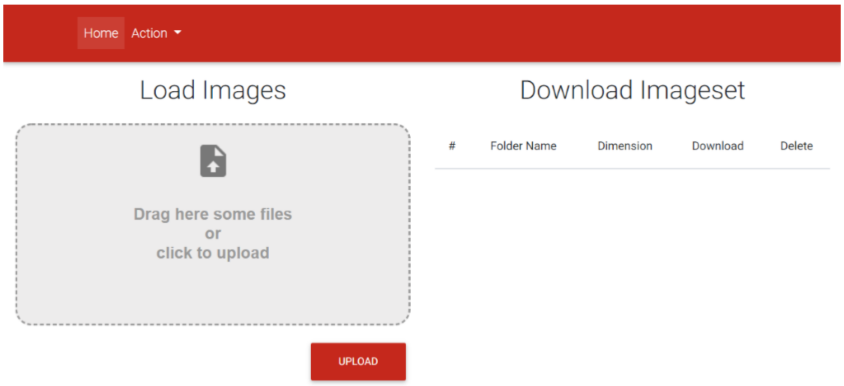
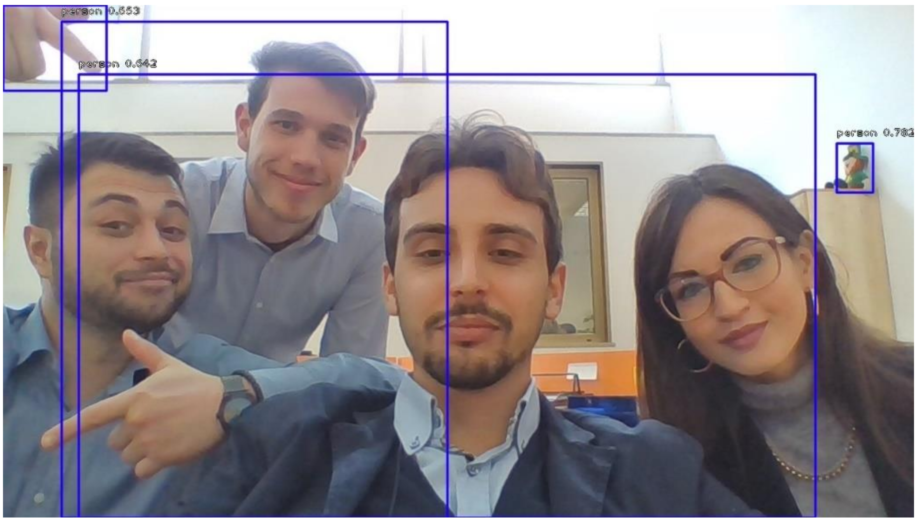


Figure 6: Image Anonymizer Visual App template

Appendix D. La mia esperienza in ELIS Consulting & Labs

Il lavoro svolto oggetto della stesura di questa tesi è frutto della mia partecipazione al programma di formazione *Junior Consulting* ed.35, promosso da ELIS Consulting & Labs, a Roma. Questa esperienza mi ha concesso la possibilità di lavorare ad un progetto con una forte componente di innovazione tecnologica, dal quale "mi porto a casa" un prezioso bagaglio di nuove competenze tecniche, nonché di *soft skills.* Credo infatti che uno dei più grandi valori aggiunti che questo percorso possa lasciarmi sia quello di vivere, e di comprendere appieno quello che è il concetto di cultura organizzativa, che si concretizza nei comportamenti, nei valori e nelle relazioni che caratterizzano in maniera unica la divisione Consulting & Labs di ELIS.



Il ricordo di un momento divertente durante un test del nostro modello di *Object Detection* sulla classe "persona" .

Lavorare su un progetto di consulenza di questo tipo significa imparare a gestire l'incertezza in un contesto mutevole ed in continuo cambiamento, significa mettersi in gioco ogni giorno, imparando a raggiungere gli obiettivi in maniera completa ma anche tempestiva. Il ruolo che più si avvicina a quello che ho personalmente ricoperto nel corso di questo progetto sia quello di *data translator,* ovvero l'interfaccia tra l'aspetto *business* delle attività e l’aspetto di sviluppo della soluzione algoritmica. Nello specifico, attraverso gli strumenti di analisi, ho sempre cercato di assicurare che le informazioni generate attraverso i test e le prototipazioni svolte nel processo di sviluppo, si traducessero in un impatto quantificabile a livello delle metriche di performance e di obiettivi definiti insieme al cliente. Le soluzioni ed i *tools* basati sui concetti di *Deep Learning* sono altamente complessi da comunicare agli stakeholders rilevanti di progetto che detengono poca conoscenza tecnica specifica in tale campo. Per questo motivo, un altro ruolo fondamentale ha riguardato la cura dell’aspetto comunicativo: ogni qual volta che sono stati presentati i risultati intermedi al cliente, è stato necessario progettare nel dettaglio tutta la fase di *reporting* e comunicazione, con l’obiettivo di esporre le informazioni in modo tale da permettere agli stakeholders di cogliere le intuizioni, e di identificare le azioni tempestive.

Durante tutta l’attività progettuale ho avuto l’occasione di collaborare con Lorenzo (Team Leader, ingegnere dell’automazione e Management Consultant presso ELIS), Cosmo (ingegnere gestionale, Analyst presso ELIS) e Antonio (ingegnere dell’automazione, anch’egli partecipante della 35ima edizione *Junior Consulting*), persone che posso reputare straordinarie, sia dal punto di vista professionale, che umano. Abbiamo raggiunto notevoli obiettivi insieme: abbiamo studiato tanto, ci siamo confrontati sugli approcci per la risoluzione dei problemi, abbiamo condiviso momenti di sconforto, ma anche momenti di soddisfazione e gratitudine reciproca. All’interno del mio team, il lavoro è stato sempre suddiviso in modo che ognuno di noi potesse svolgere attività in linea con i propri punti di forza, e apportare quindi il proprio valore aggiunto, sentendosi parte di un sistema sinergico e non composto da singoli elementi.

Fase	***Competenze tecniche acquisite***	***Strumento***
Data Preparation and Functional Architecture Analysis	Overview sui modelli algoritmici allo stato dell’arte per svolgere operazioni di *Object Detection*	
	Teoria e funzionamento del modello di *Object Detection* RetinaNet	Framework TensorFlow Libreria Python Keras
	Preparazione dataset di immagini per l’allenamento del modello RetinaNet	Software LabelImg
Training e Validation of the Object Detection Algorithm	Implementazione della funzionalità di *blurring* all’interno del modello di RetinaNet	Libreria Python OpenCV

Competenze tecniche e strumenti acquisiti nel percorso di tesi.

I regali più belli che ho ricevuto in questi cinque mesi sono stati quelli di lavorare con passione ogni singolo giorno e di comprendere quale fosse l’ambito che mi piacerebbe approfondire nel mio prossimo futuro professionale: il mondo del *Data Analytics*. Non posso che essere grata e onorata di aver avuto l’opportunità di iniziare il mio percorso nel mondo del lavoro (e forse anche nel mondo) in questo modo.