

Handwritten SigNature forgery detection

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min

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5 min

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0 Introduzione

Introduzione



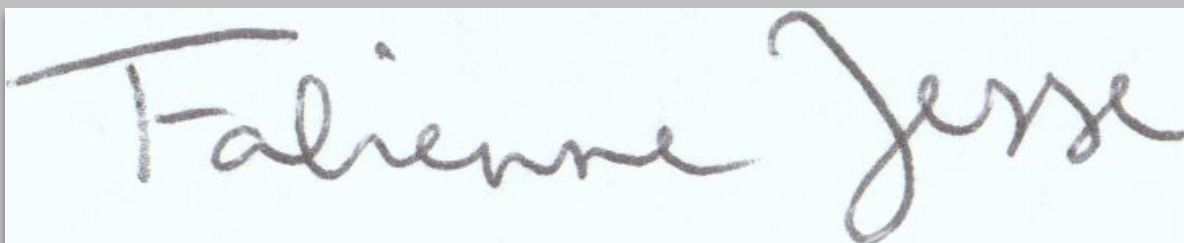
La firma a mano libera è una **caratteristica biometrica**. Es. impronta digitale, la retina e la voce.



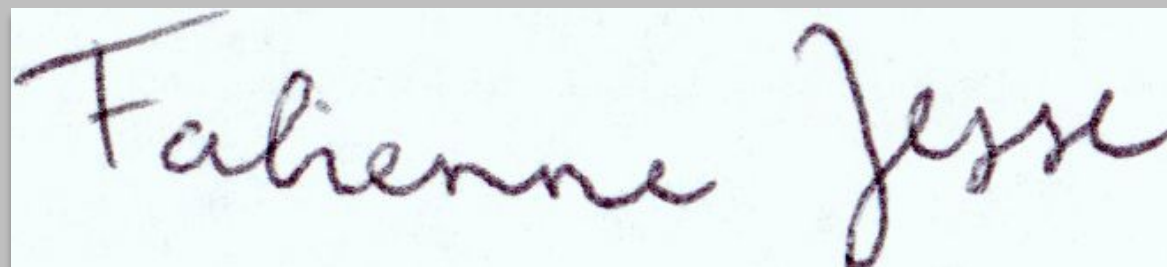
Rappresentazioni: firma statica (**offline**) vs firma dinamica (**online**)



Contraffazioni: firma cieca (**blind**), firma semplice (**simple**), firma esperta (**skilled**), tracciamento (**tracing**) e trasferimento ottico (**optical transfer**).



Esempio autentico



Esempio contraffatto

Introduzione



Le firme genuine di un utente possono essere molto variabili tra loro, l'**inconsistenza** di un utente nella scrittura rende difficile verificare le firme esperte (**skilled**)



Il nostro obiettivo è creare, valutare e comparare gli approcci **writer dependent** e **writer independent** al problema della forgery detection, nel contesto di esempi statici (**offline**).

Writer dependent



Quando gli utenti presenti nel testing **sono** già stati elaborati in fase di training

Writer independent



Quando gli utenti presenti nel testing **non sono** stati elaborati in fase di training



La nostra **ipotesi** è che i sistemi writer dependent siano più accurati dei modelli writer independent, ma richiedano più risorse (numero di esempi, tempi di addestramento)

Tabella dei contenuti

1 Preparazione dei dati

Preparazione dei dati

CEDAR 2640



N.utenti: 55

Genuine: 24

Contraffatte: 24

Dr. Am. Beach

KAGGLE 300



N.utenti: 30

Genuine: 5

Contraffatte: 5

Esposito

ICDAR 2294



N.utenti: 60

Genuine: 12

Contraffatte: 24

Joe Martin

Preparazione dei dati

CEDAR 2640



KAGGLE 300



ICDAR 2294



Id remapping

Preprocessing

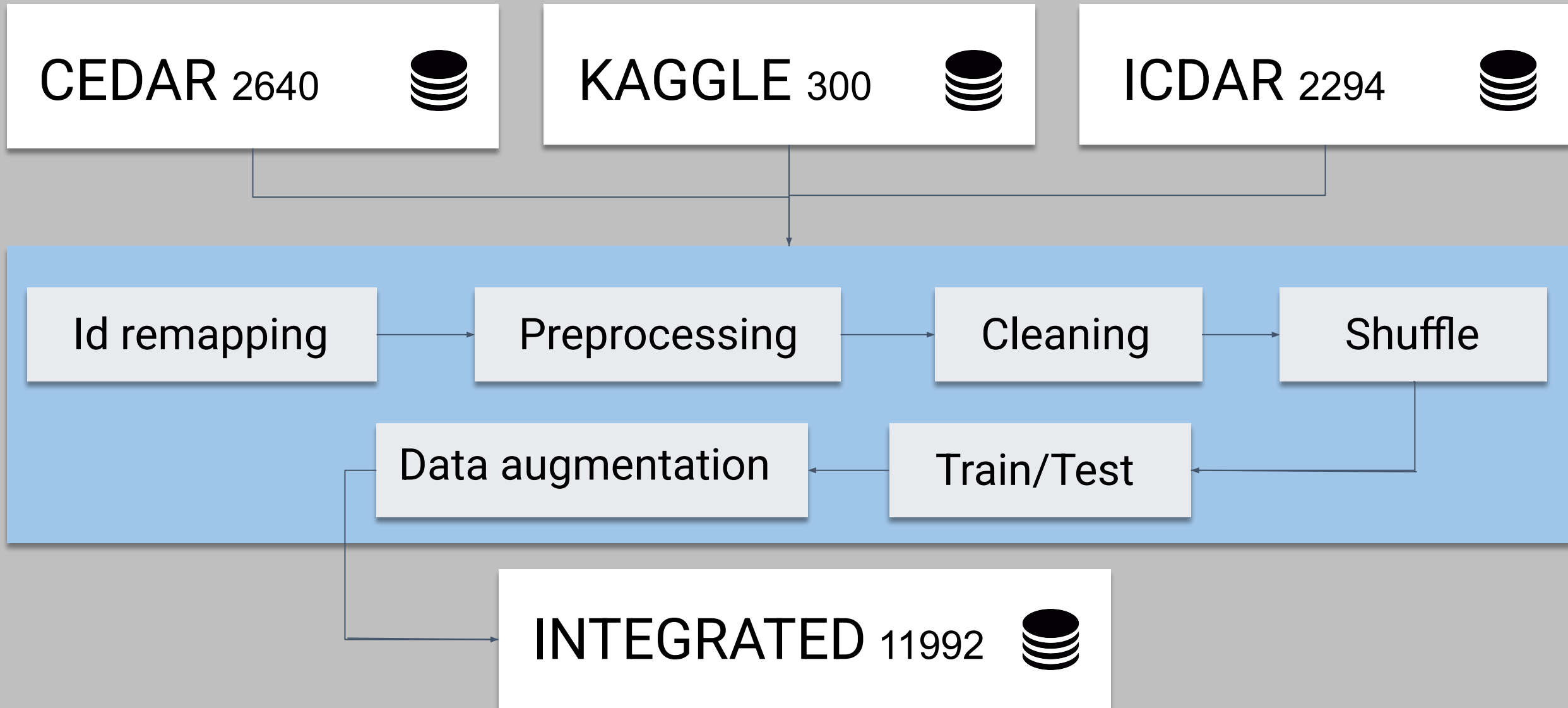
Cleaning

Shuffle

Data augmentation

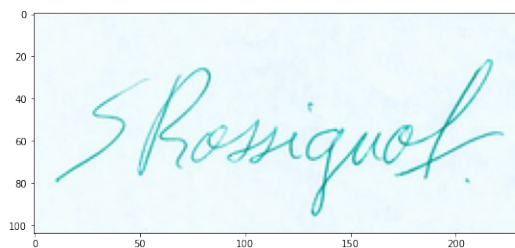
Train/Test

INTEGRATED 11992

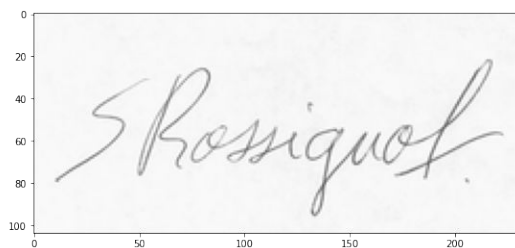


Preparazione dei dati

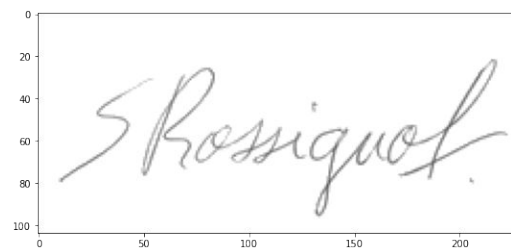
PREPROCESSING



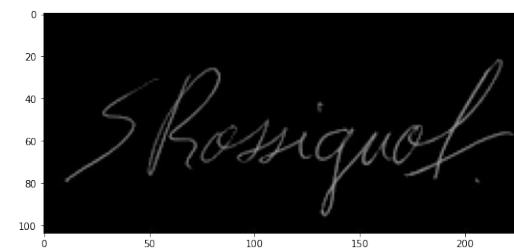
Originale



Grayscale



Thresholding



Inversion

AUGMENTATION



CLEANING

Preservazione degli utenti con immagini di dimensione almeno **128 x 256**.

Il dataset integrato presenta **109 utenti**,
cioè l'85% degli utenti precedenti

Approcci: Writer dependent vs Writer independent

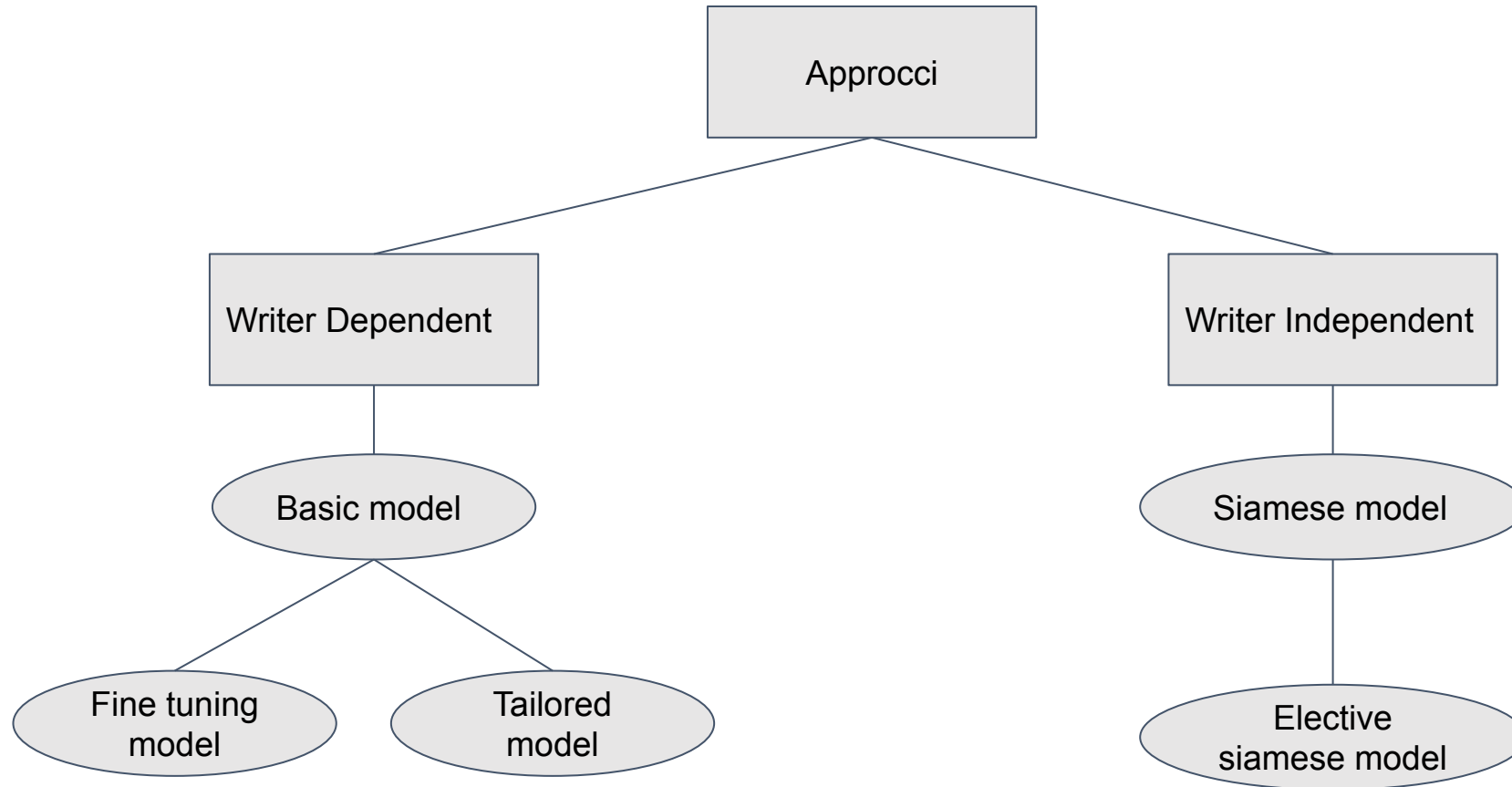
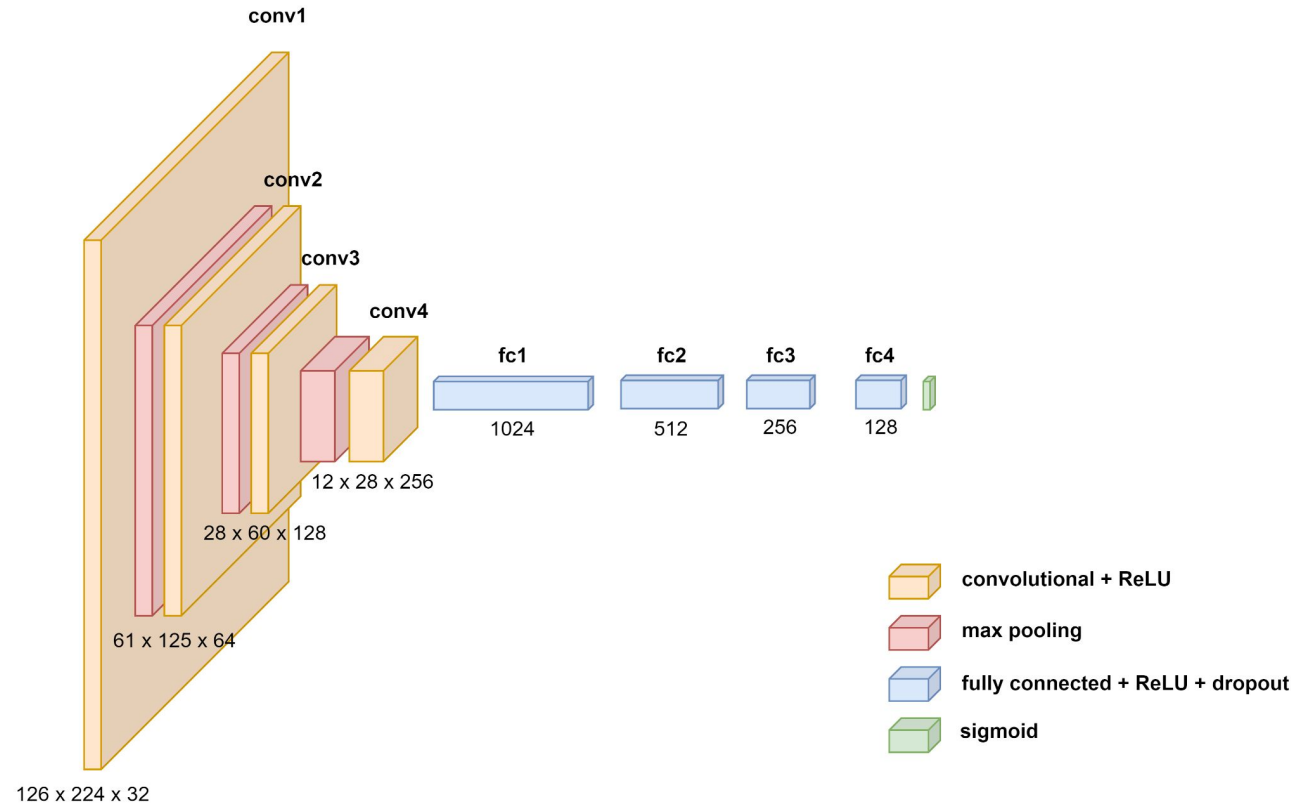


Tabella dei contenuti

2 Writer dependent

Writer Dependent | Basic model



IPERPARAMETRI

Batch size: 128

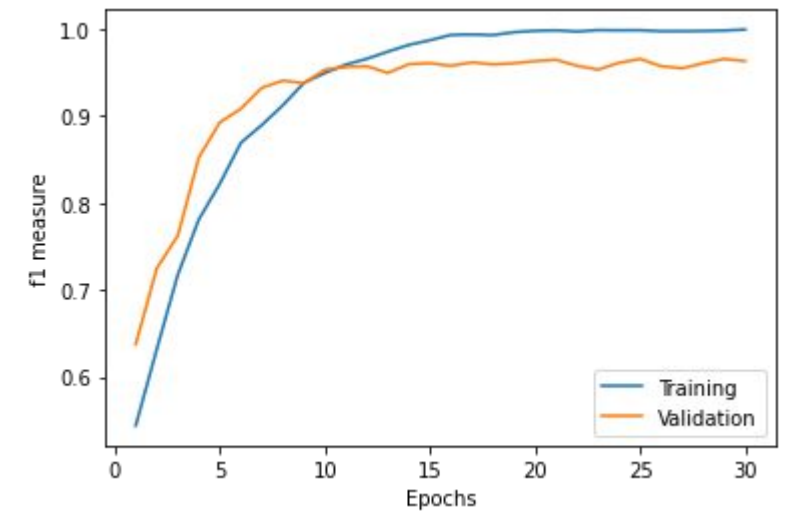
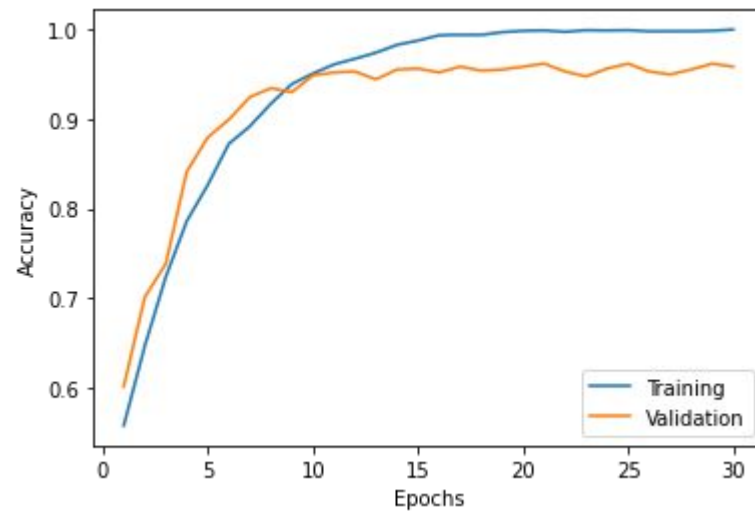
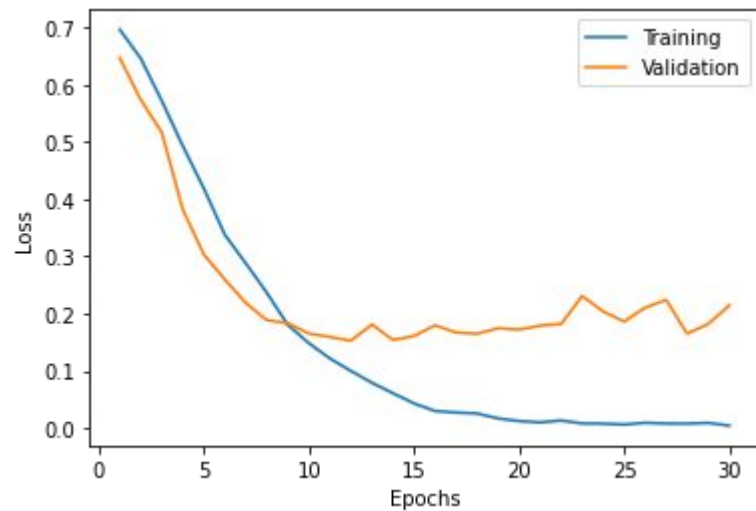
Epochs: 30

Optimizer: Adam

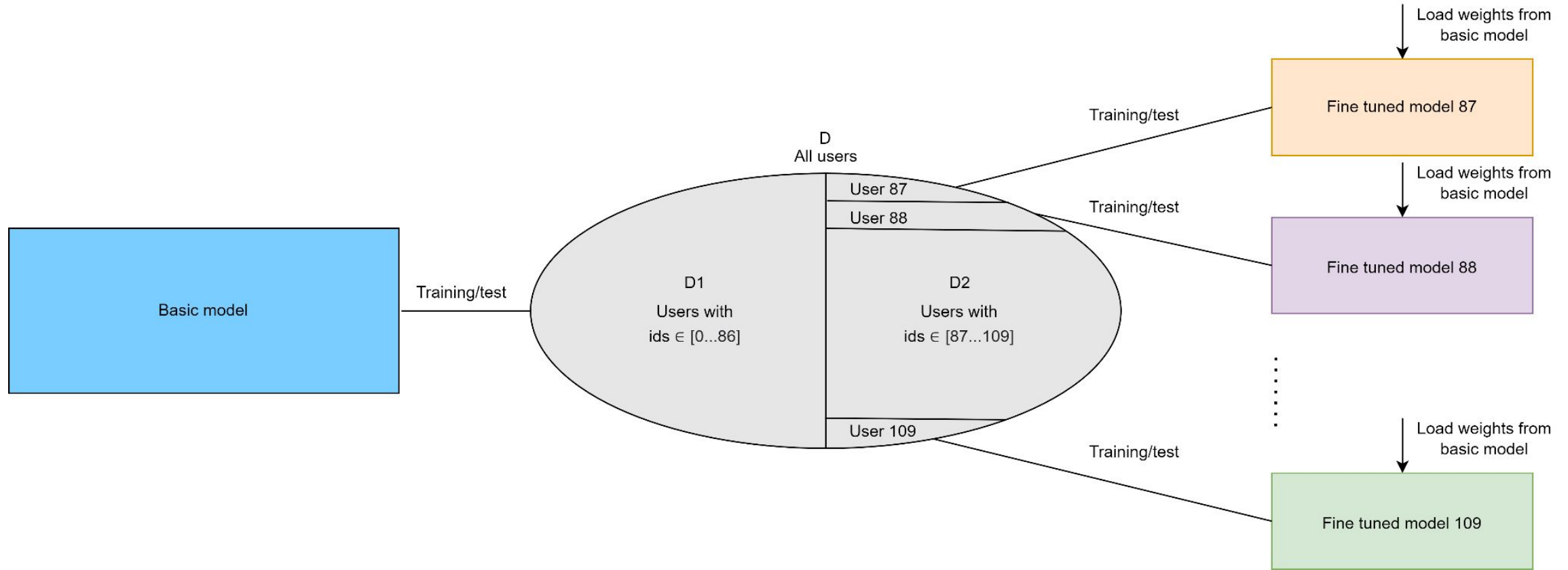
Learning rate: 0.00003

Dropout rate: 0.3

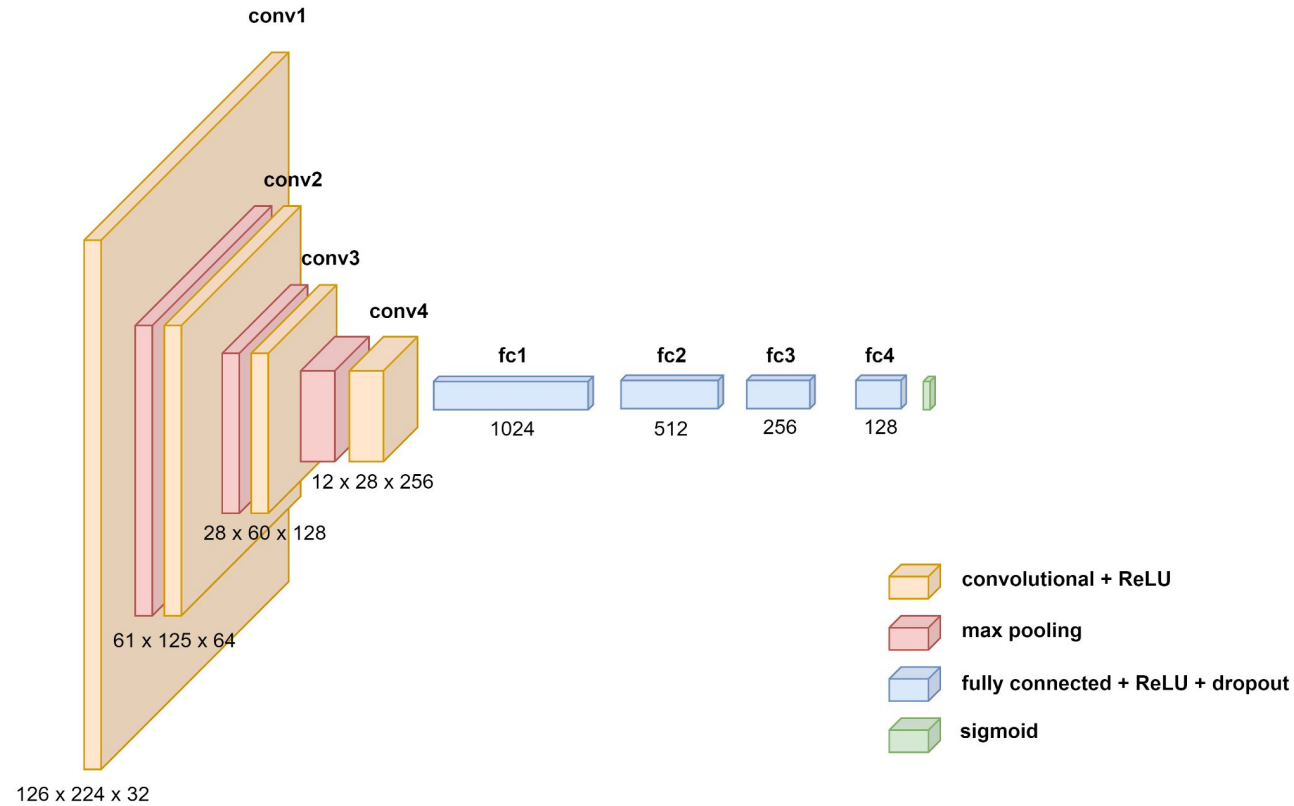
Basic model | Analisi Training/Validation



Writer Dependent | Fine tuning model



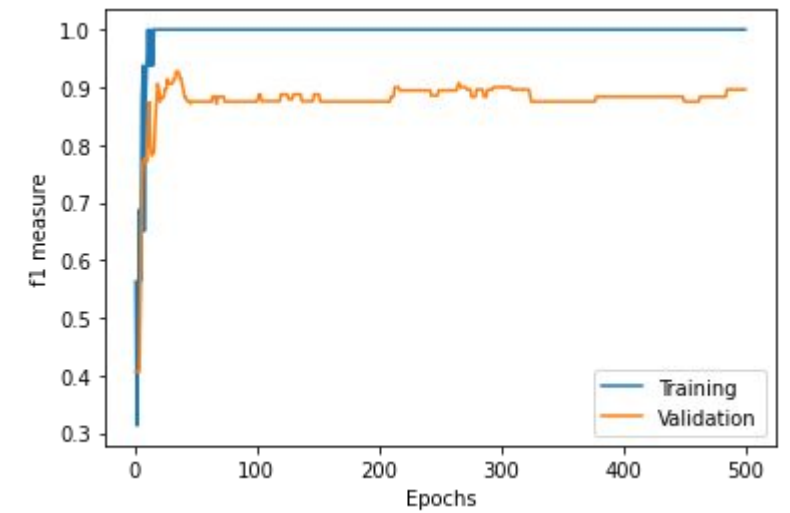
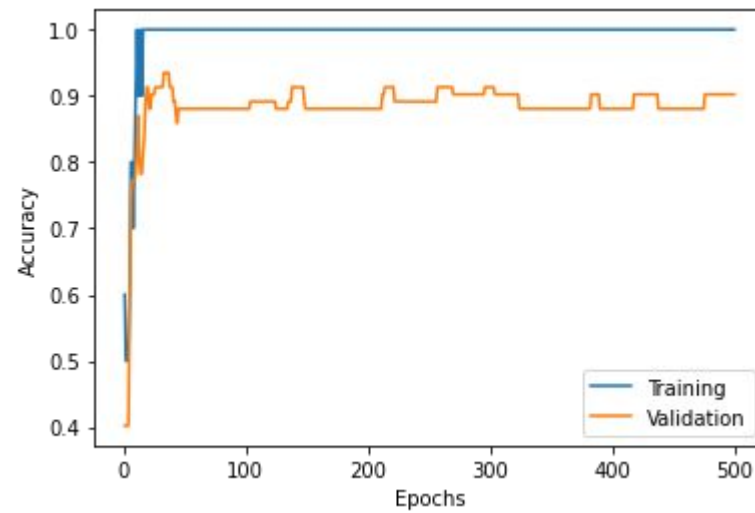
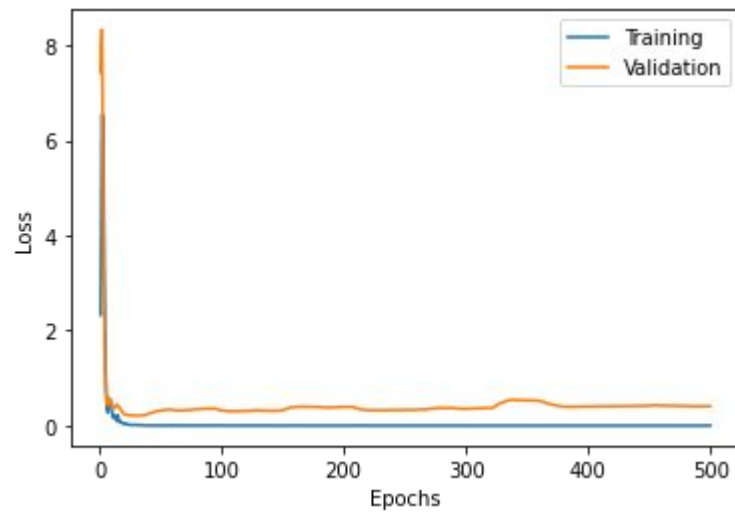
Writer Dependent | Fine tuning model



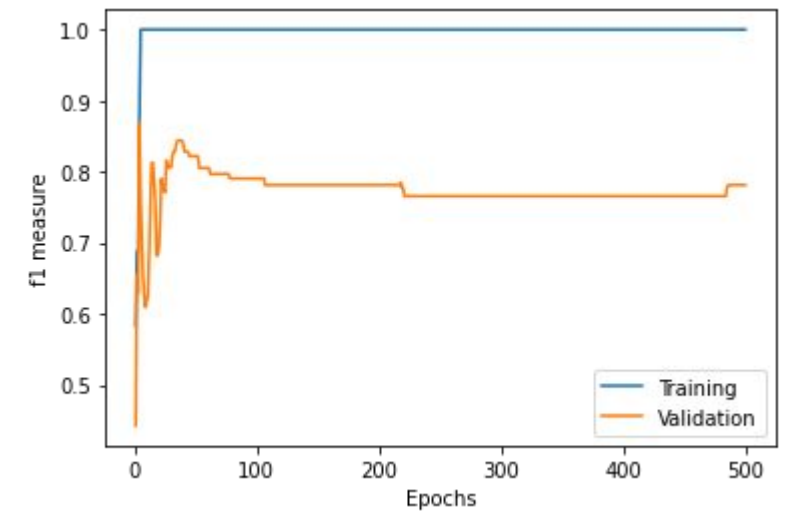
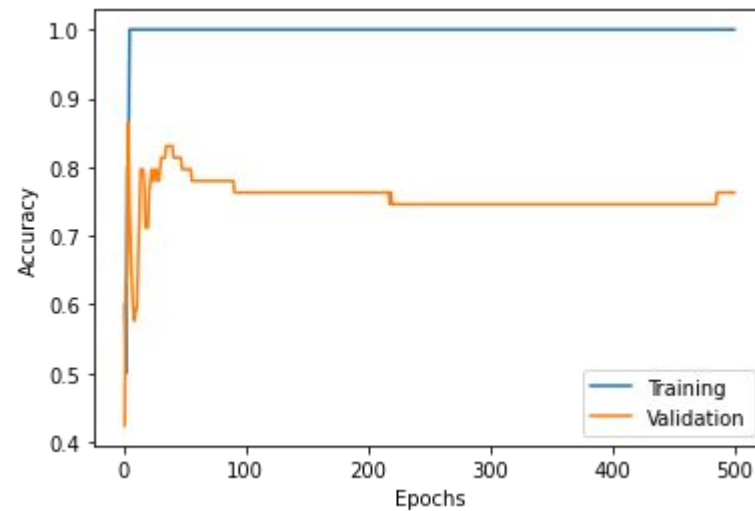
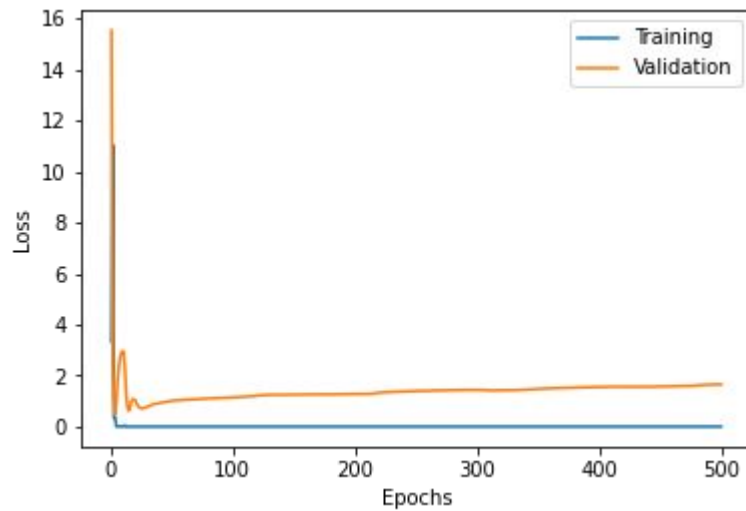
IPERPARAMETRI

Batch size: x **Epochs:** 500 **Optimizer:** Adam **Learning rate:** 0.00003 **Dropout rate:** 0.3

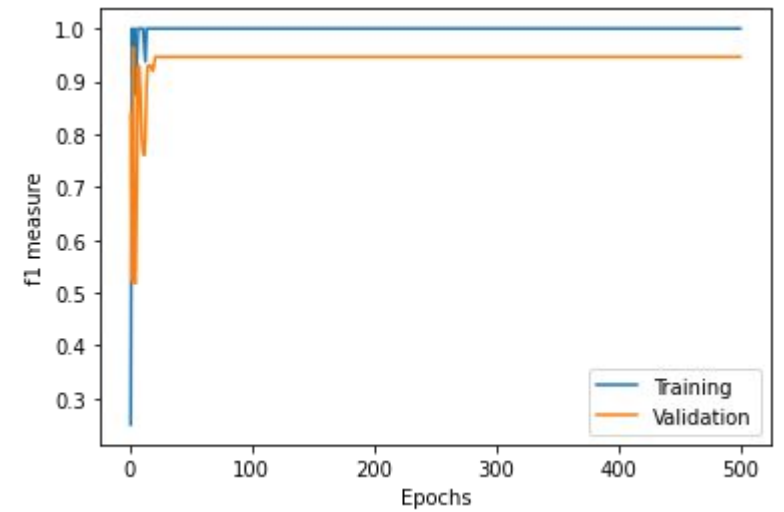
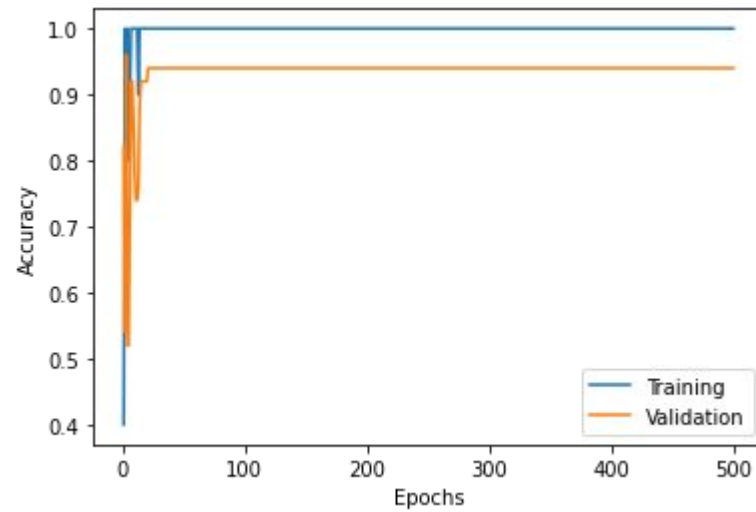
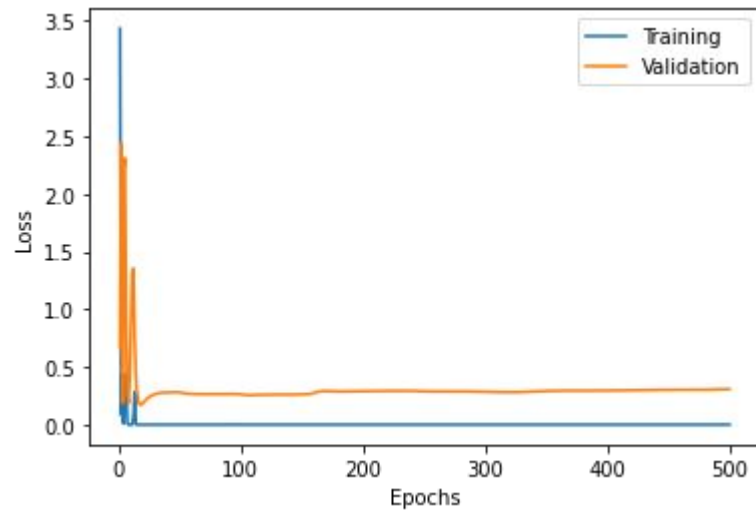
Fine tuning model | Analisi Training/Validation | User 87



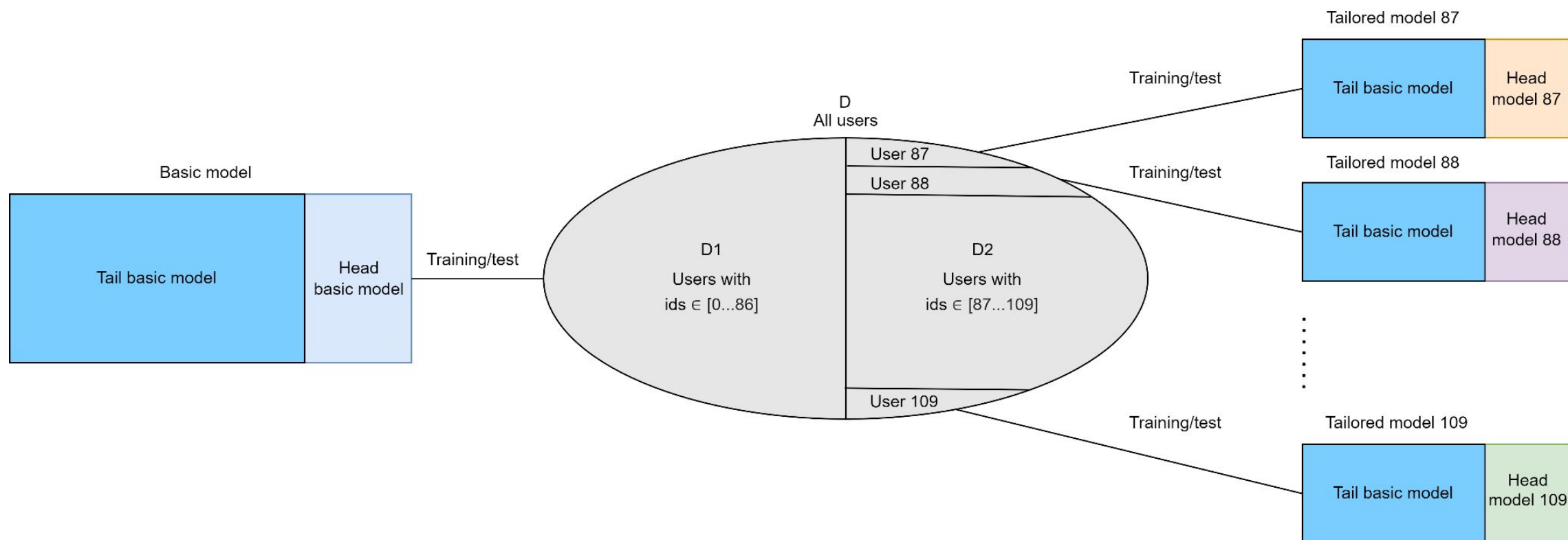
Fine tuning model | Analisi Training/Validation | User 88



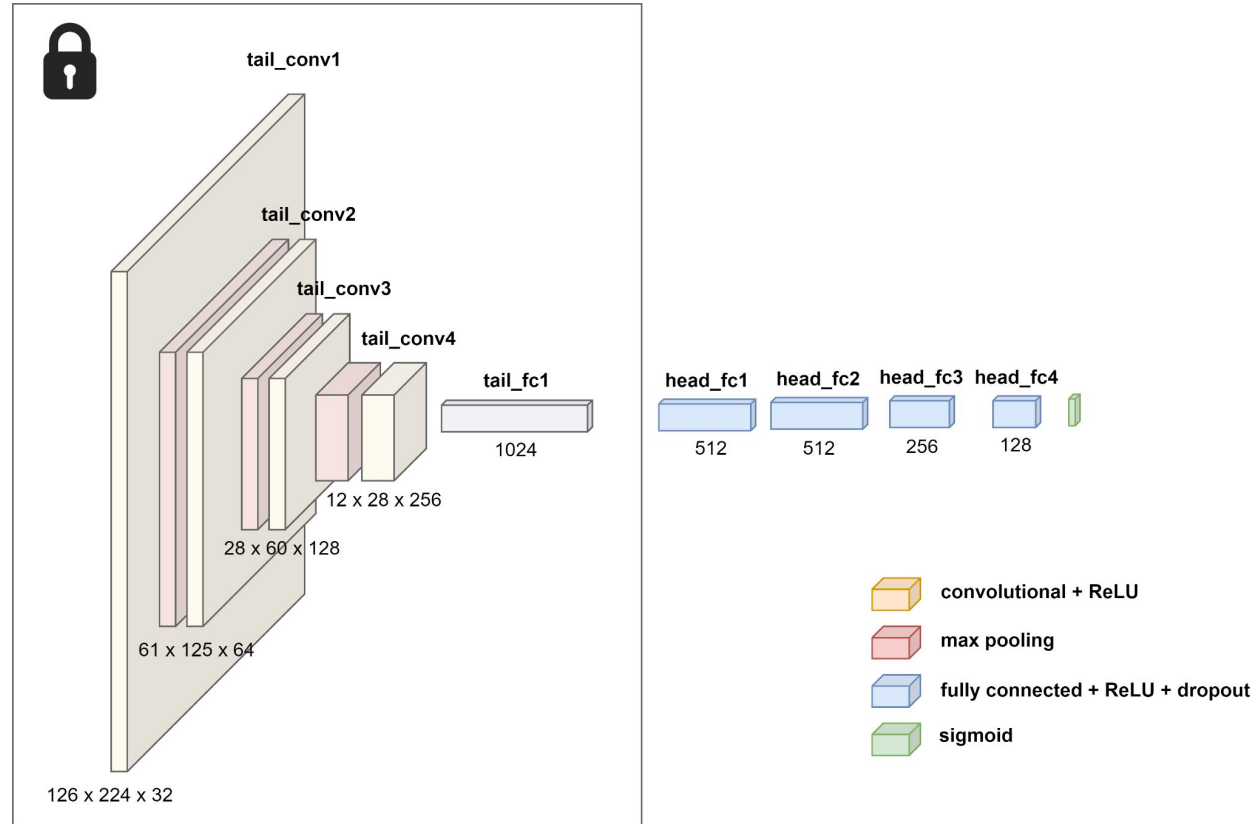
Fine tuning model | Analisi Training/Validation | User 89



Writer Dependent | Tailored model



Writer Dependent | Tailored model



IPERPARAMETRI

Batch size: x

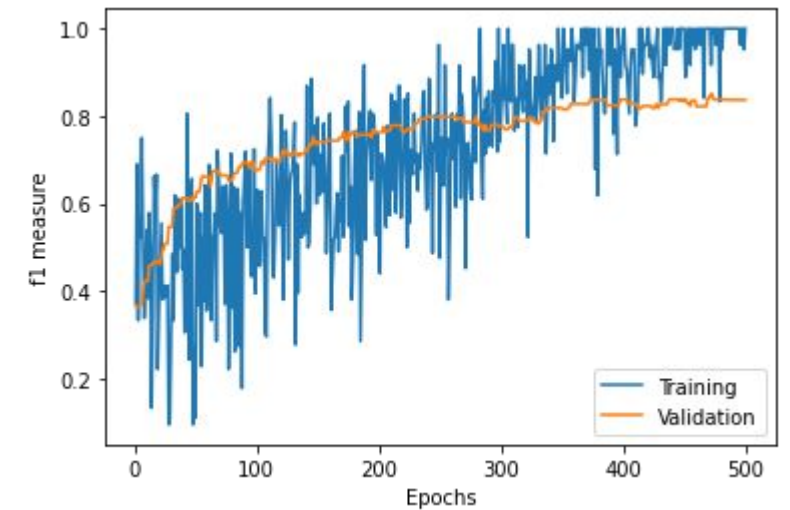
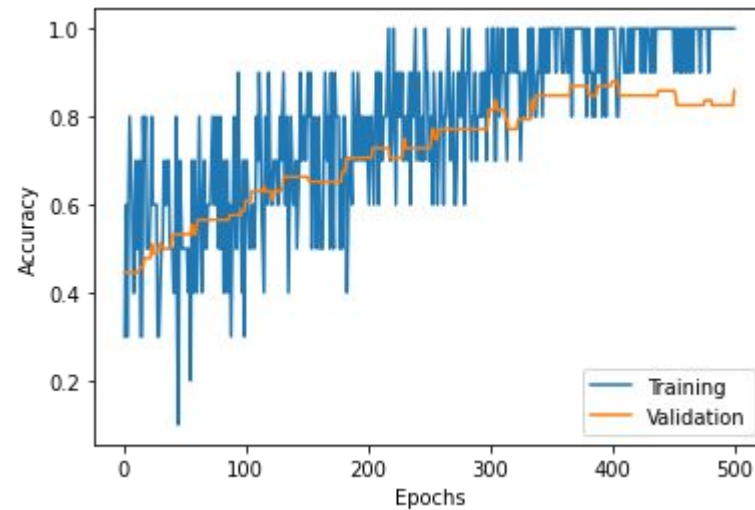
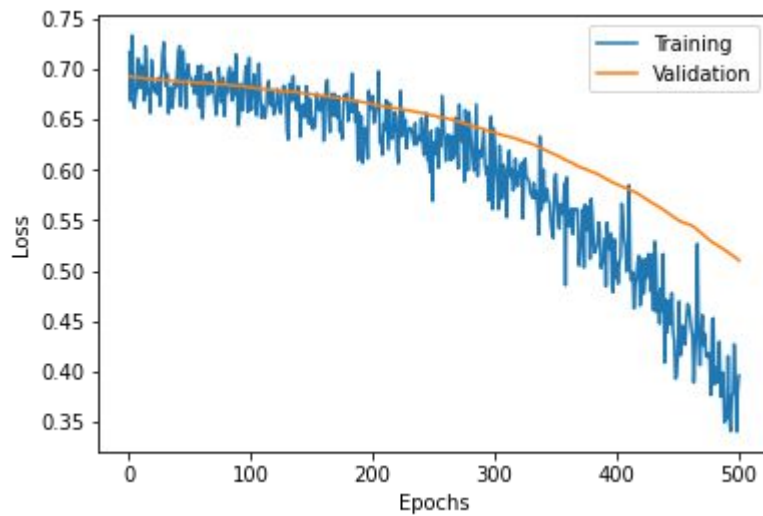
Epochs: 500

Optimizer: Adam

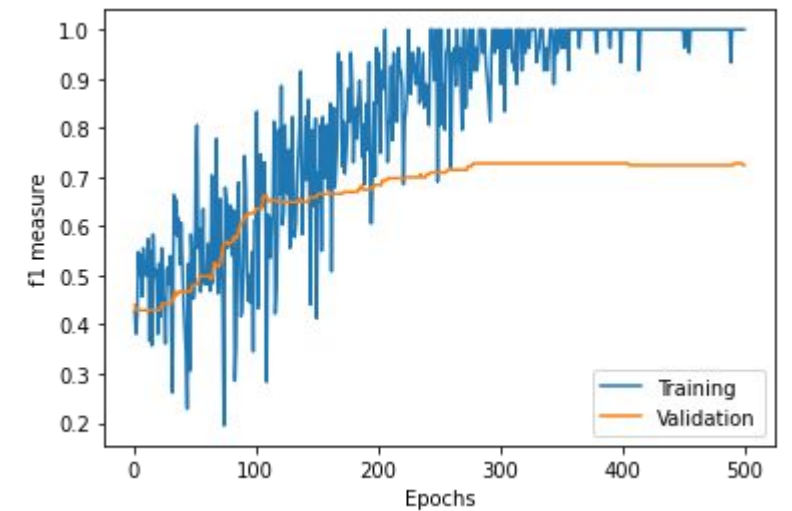
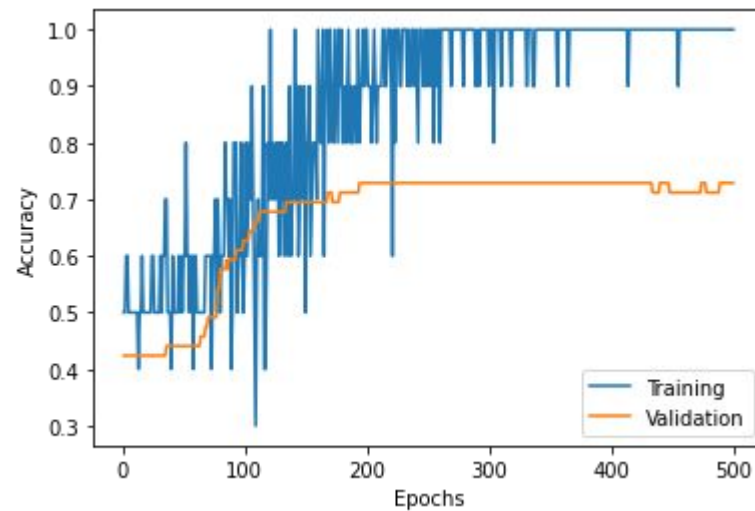
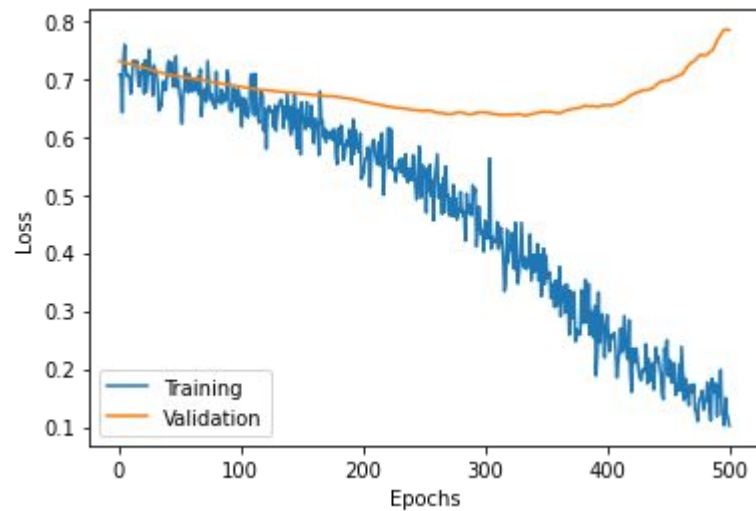
Learning rate: 0.00001

Dropout rate: 0.4

Tailored model | Analisi of Training/Validation | User 87



Tailored model | Analisi of Training/Validation | User 88



Tailored model | Analisi of Training/Validation | User 89

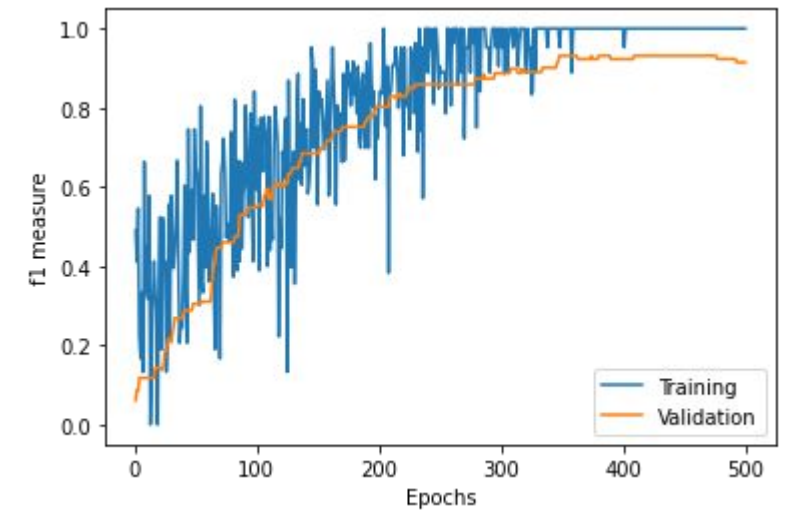
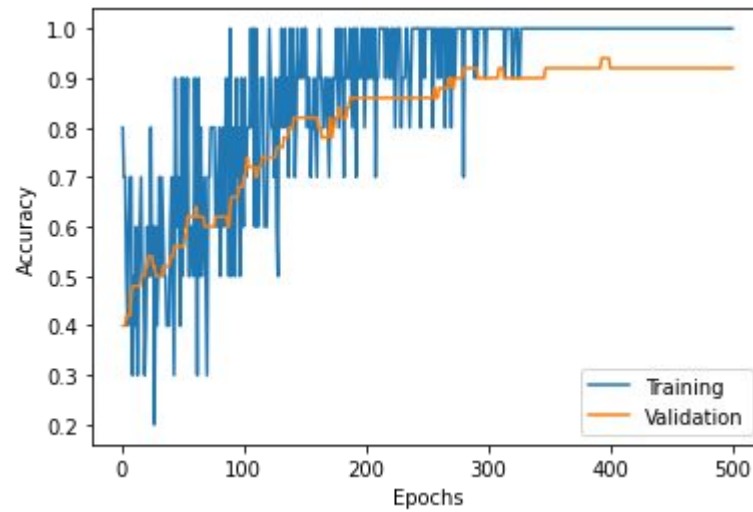
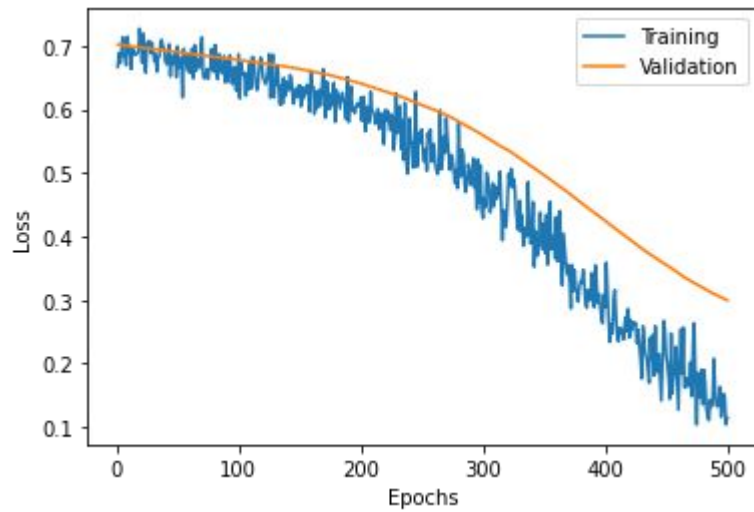
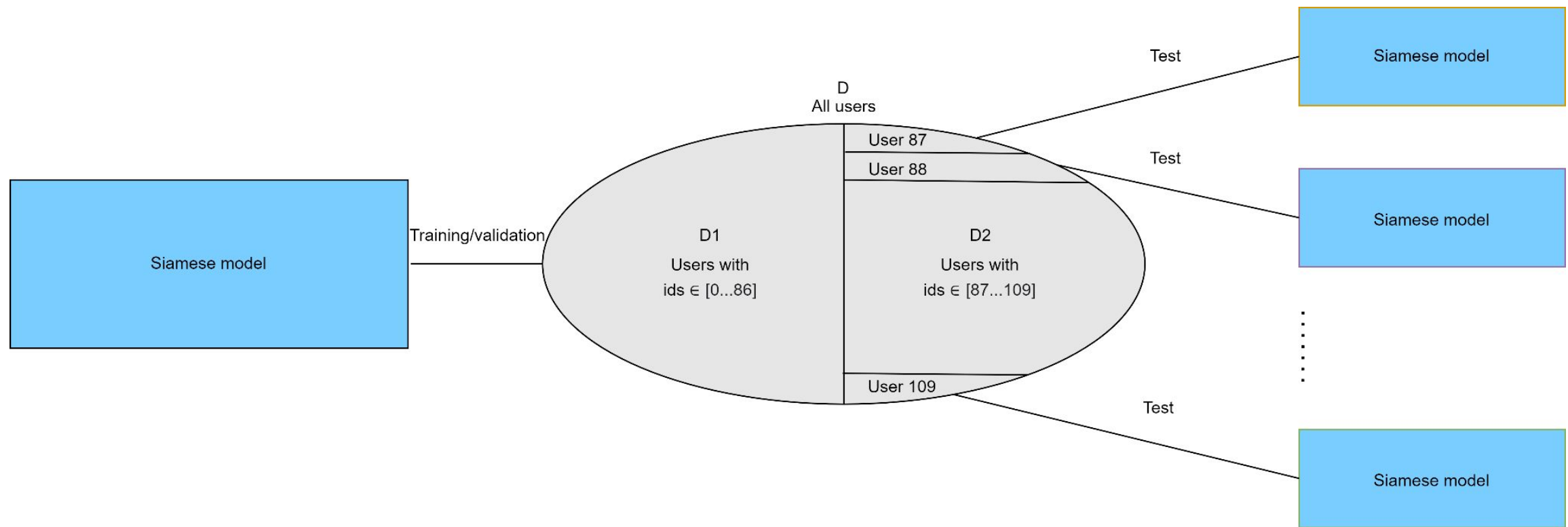


Tabella dei contenuti

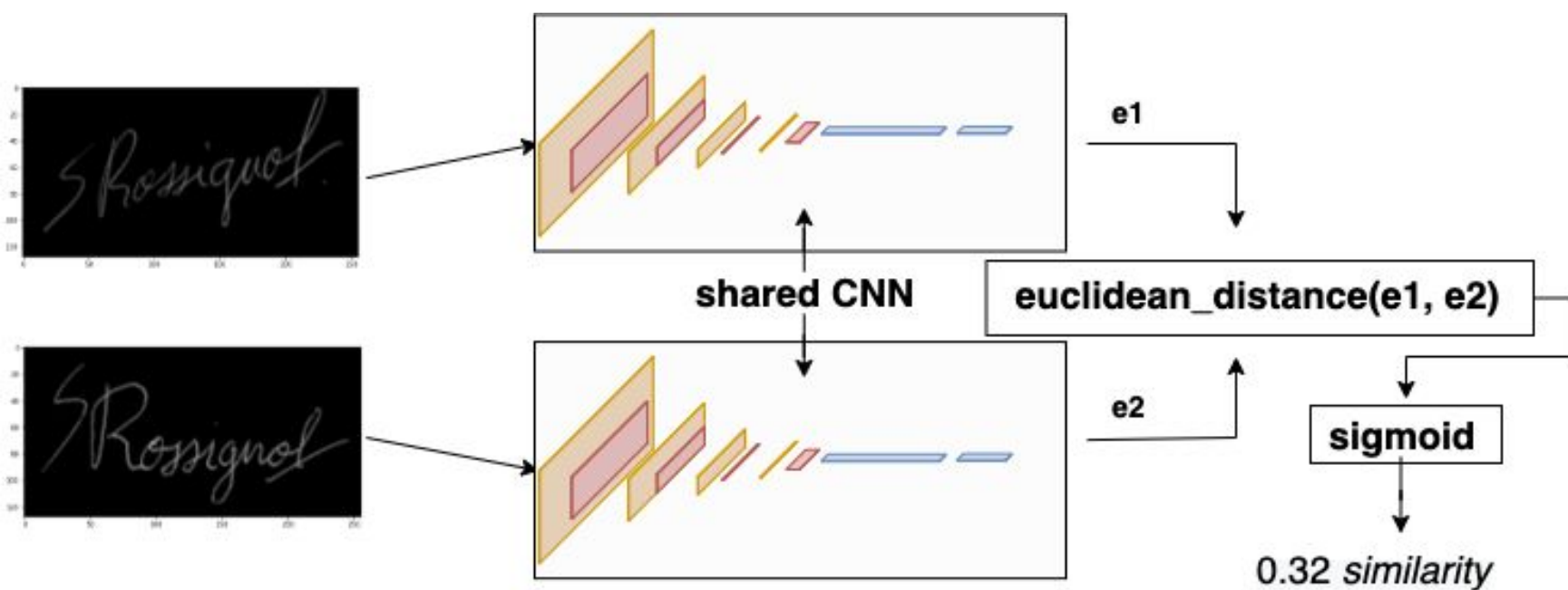
3 Writer independent

Writer independent | Siamese model

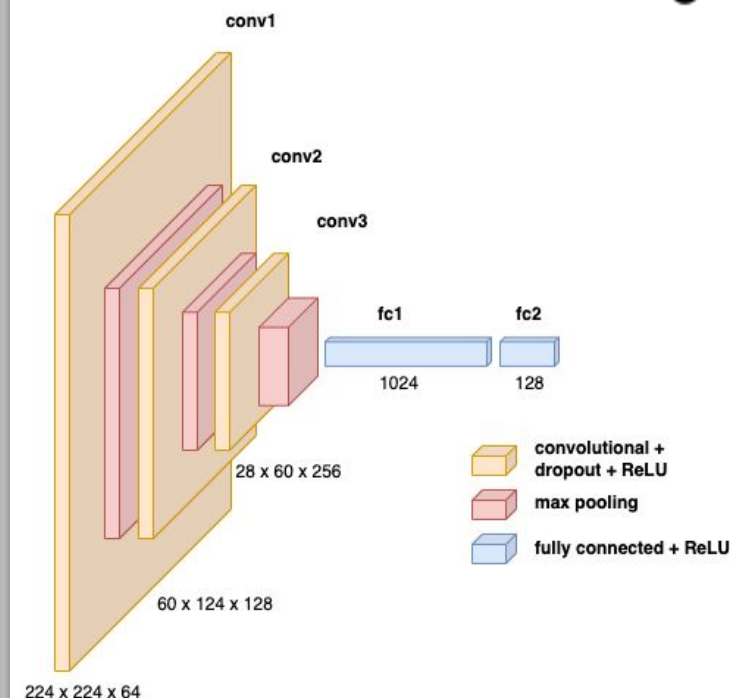


Writer independent | Siamese model

RETE SIAMESE



CNN



IPERPARAMETRI

Batch size: 32

Epochs: 15

Optimizer: Adam

Learning rate: 0.00006

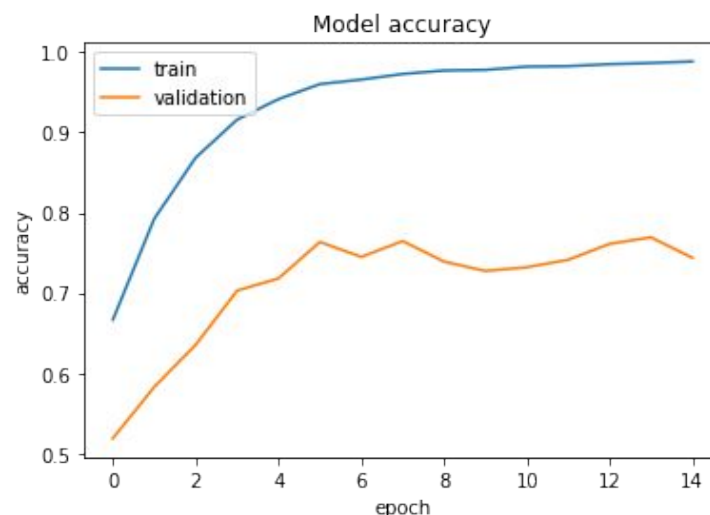
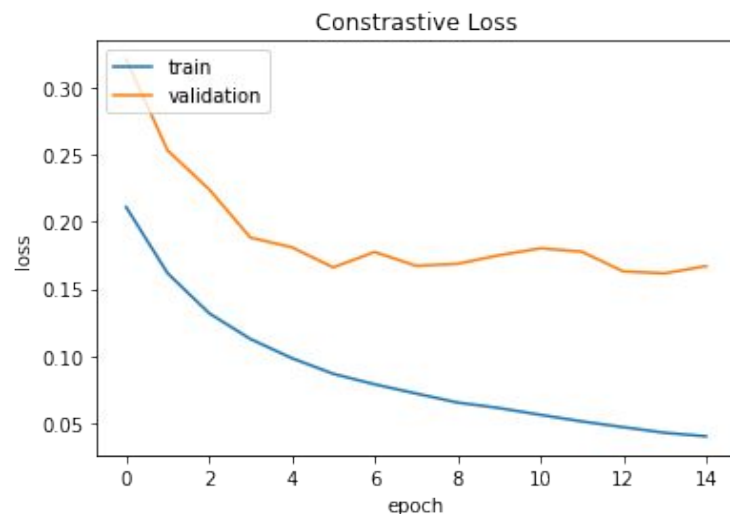
Margin: 1

Writer independent | Siamese model

CONTRASTIVE LOSS



$$L(r_0, r_1, y) = y(d(r_0, r_1)) + (1 - y)\max(0, m - d(r_0, r_1))$$



DISTANZA EUCLIDEA

La **distanza** euclidea viene calcolata tra i due embeddings in uscita dalle CNN condivise.

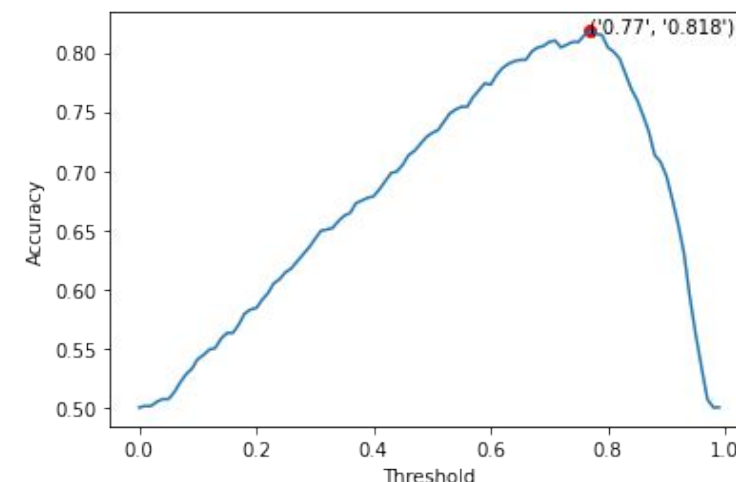
$$d(r_0, r_1) = \|r_0 - r_1\|_2$$

NEGATIVE SELECTION



Le coppie facili, cioè quelle coppie di immagini che producono una loss pari a 0, sono state escluse dall'addestramento

THRESHOLD



Writer independent



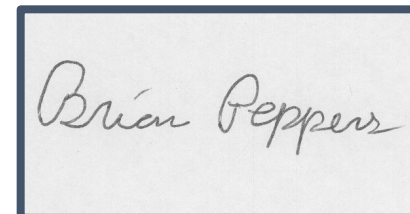
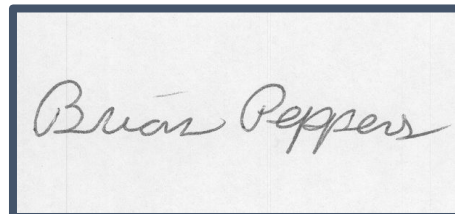
One-shot learning, è sufficiente un solo esempio di firma genuina !

Data in input la coppia di immagini (**genuina, x**) restituisce **1** se x è genuina, **0** altrimenti

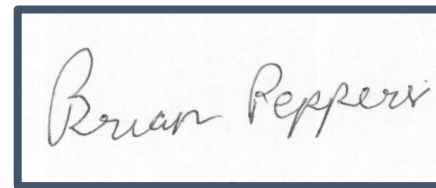
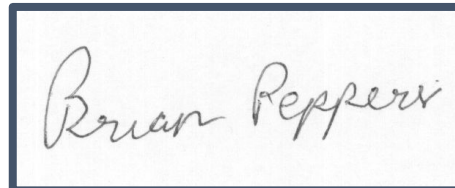
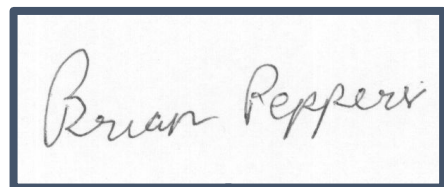


Nel caso si abbiano a disposizione più firme genuine, allora si possono indire le **elezioni**

GENUINA



x



0 - contraffatta

0 - contraffatta

1 - genuina



Le elezioni permettono di classificare un'istanza in maniera **robusta**, confrontandola con più genuine

Writer Independent | Election siamese model

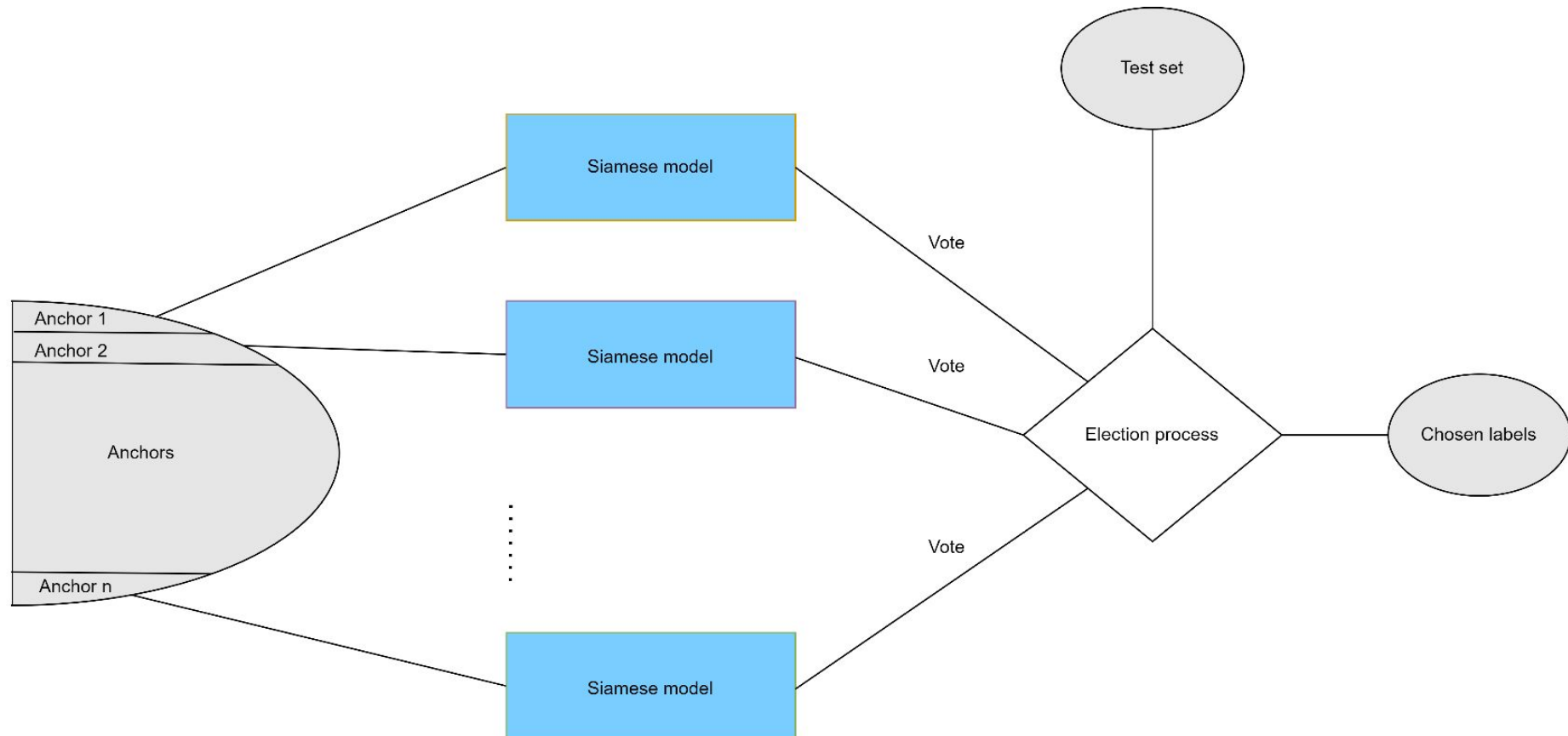


Tabella dei contenuti

4 Risultati e valutazioni

Election model | Approximated accuracy

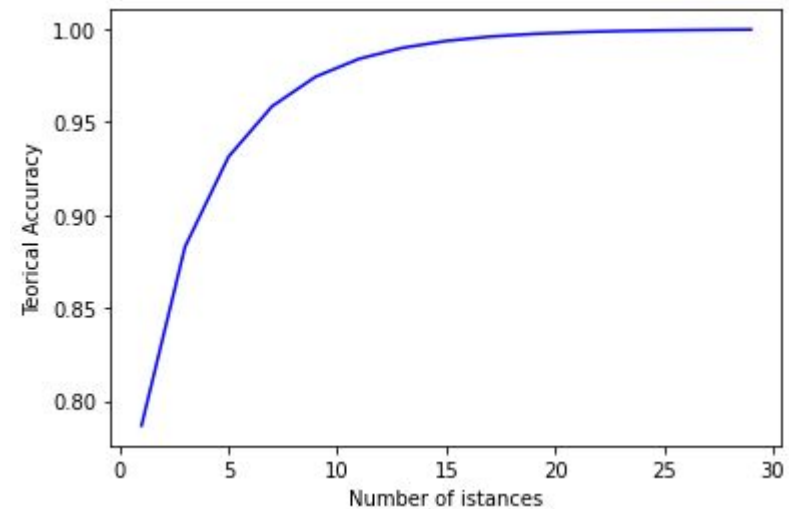
Dato un insieme di ancore $\mathbf{A} = \{\mathbf{A}_1, \mathbf{A}_2, \dots, \mathbf{A}_n\}$, il modello Siamese \mathbf{S} , l'istanza \mathbf{x} ed $\mathbf{L}(\mathbf{x})$ la relativa label.

Assumendo che:

- $\forall i P(\mathbf{S}(\mathbf{A}_i, \mathbf{x}) = \mathbf{L}(\mathbf{x})) = p$, dove p è l'accuracy media di \mathbf{S} per le varie ancore;
- $\forall i, j : i \neq j, P(\mathbf{S}(\mathbf{A}_i, \mathbf{x}) = \mathbf{L}(\mathbf{x}))$ è indipendente da $P(\mathbf{S}(\mathbf{A}_j, \mathbf{x}) = \mathbf{L}(\mathbf{x}))$;

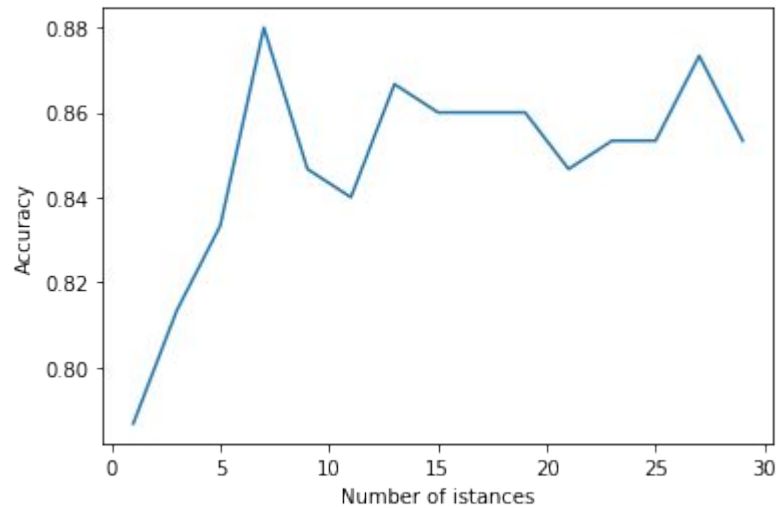
Allora l'accuracy (approssimata) del' Election model con n ancore è:

$$P_A = \sum_{k=\lfloor \frac{n}{2} \rfloor + 1}^n \binom{n}{k} p^k (1-p)^{n-k}$$

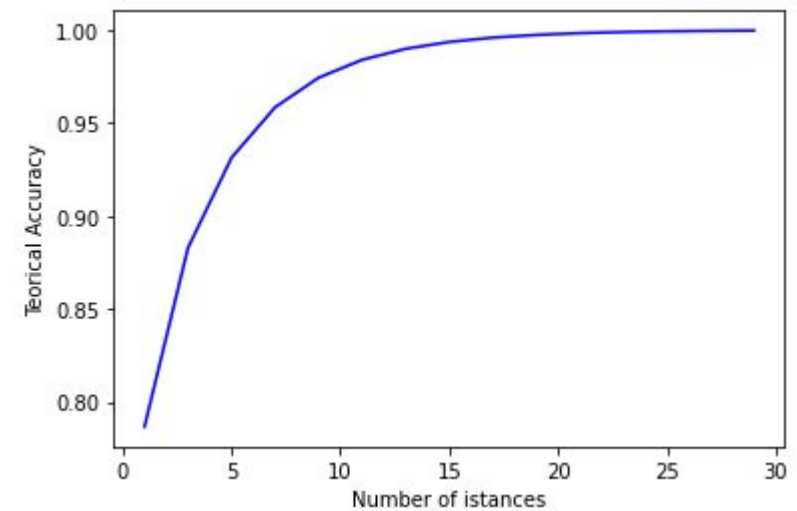


Approximated accuracy

Election model | Approximated vs experimental accuracy



Experimental accuracy

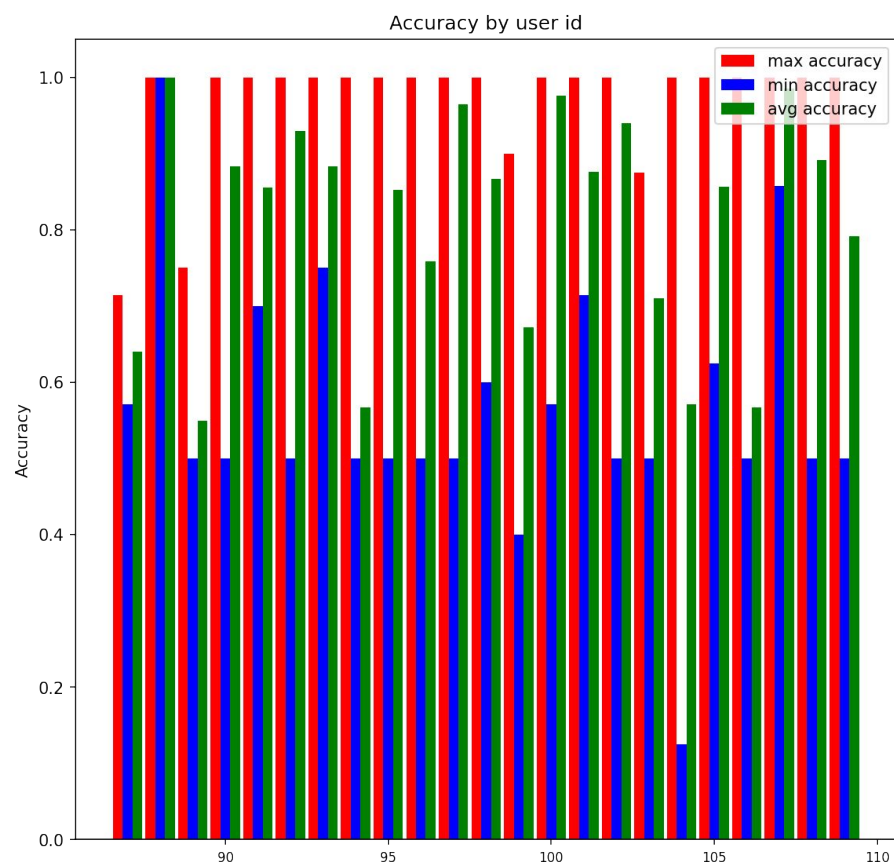


Approximated accuracy

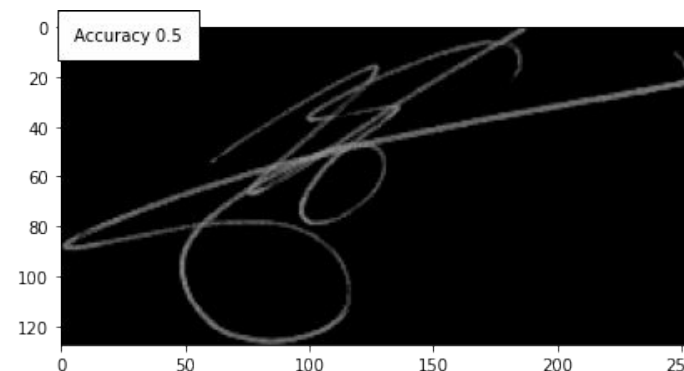
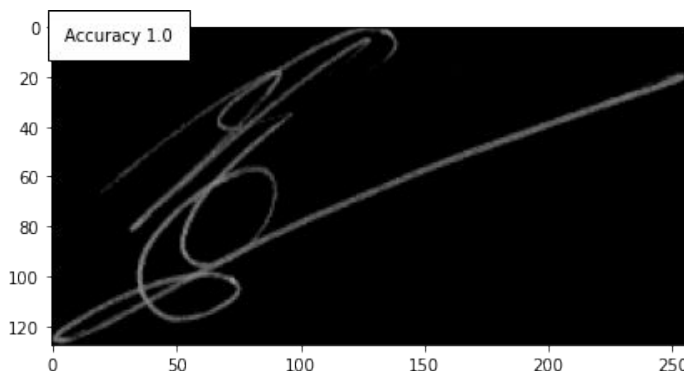
Valutazione ancora per Siamese model



Mentre l'elezione mantiene fissa l'immagine di test e rende l'ancora variabile, la **valutazione** mantiene fissa l'ancora e rende variabile l'immagine di test.



Per ogni utente e per ogni ancora (genuina) viene testata l'accuratezza sul test set



L'accuratezza minima, media e massima sono un **indicatore** della consistenza di scrittura di un utente

Utente 88 | Inter-class similarity nel training set



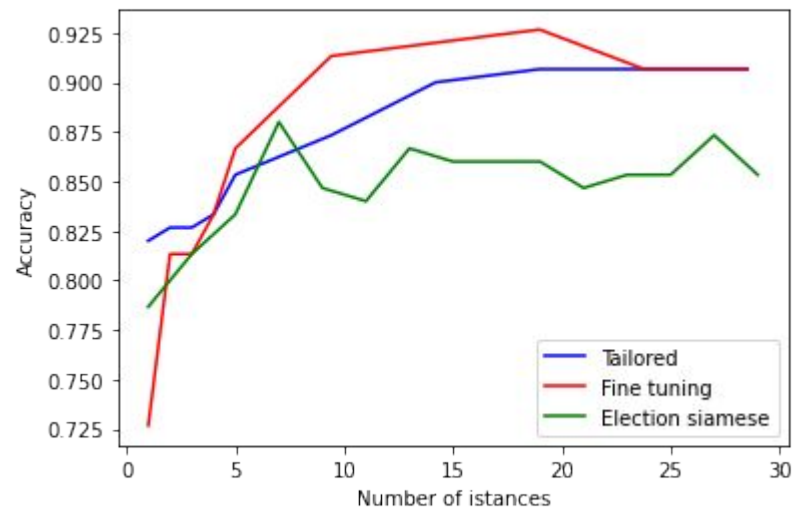
Genuine



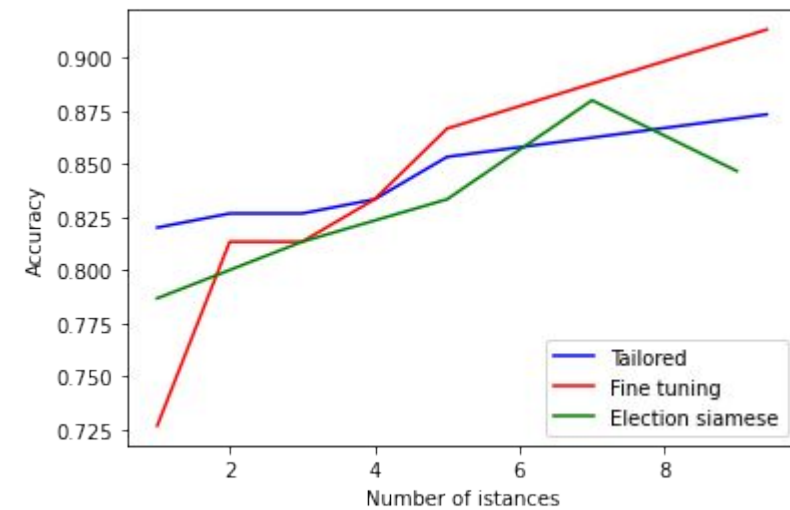
Forged



Models comparison | Accuracy per n° di istanze per utente



Range di istanze : [0,30]



Range di istanze : [0,10]

Models comparison | Tempo di training (per utente)

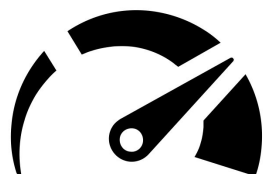
Model	Tempo medio di training per singolo utente
Fine tuning	968,5 s
Tailored	39,7 s
Siamese	None

* Assunto il numero di istanze genuine per il training pari a 5

Tabella dei contenuti

5 Conclusioni

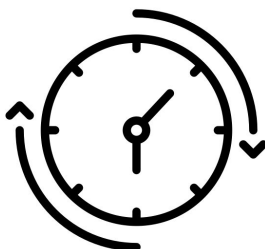
Conclusioni | Valutazione dei modelli



Il modello **fine tuning** presenta le migliori performance (a patto di avere un dataset sufficientemente grande) ma costi di training maggiori.

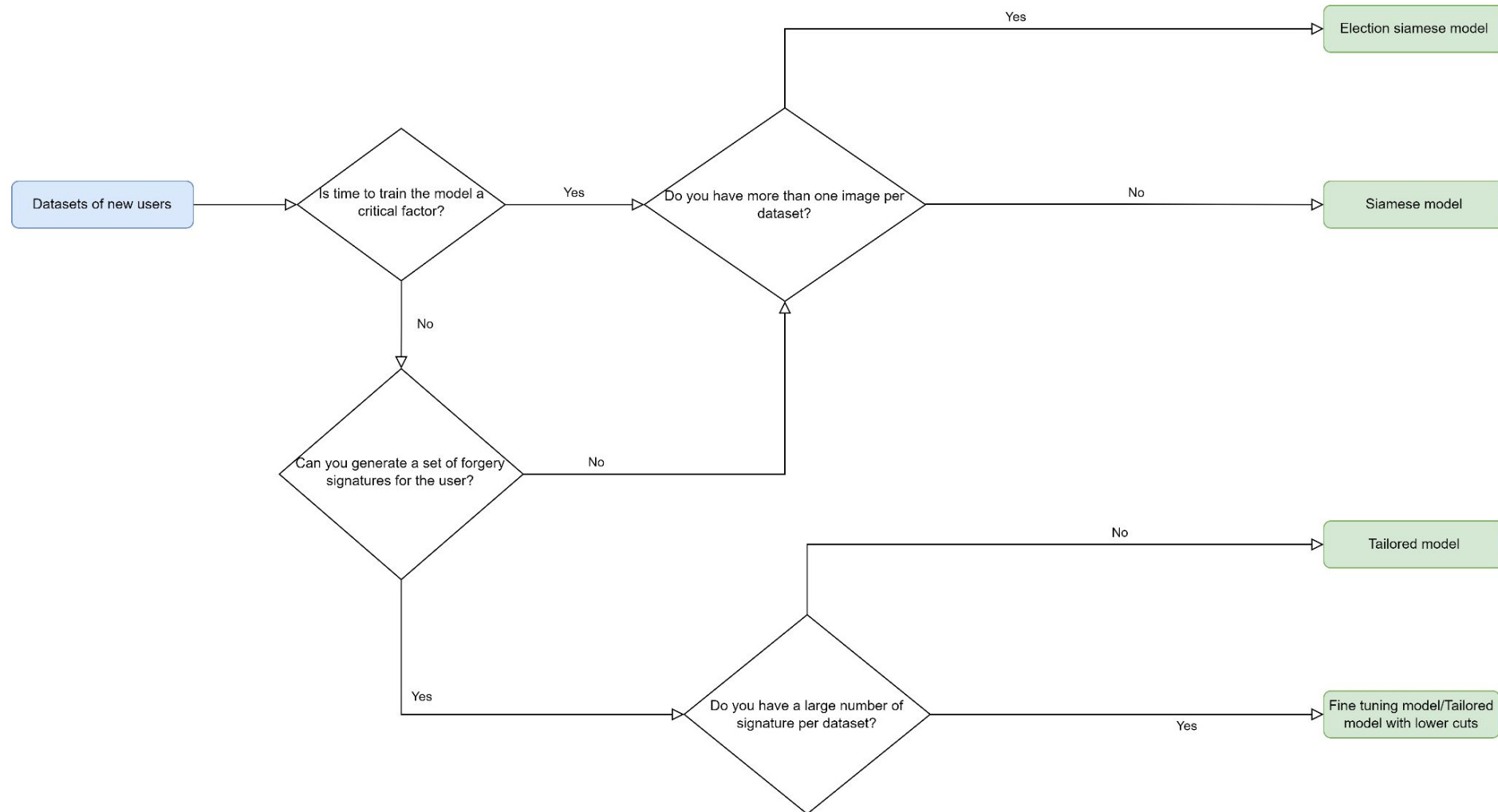


Il modello **tailored** è un buon compromesso tra performance e costi.
E' probabilmente la scelta migliore se si ha la possibilità di trainare e si vogliono ottenere buone performance in poco tempo.



Il modello **siamese** ha costi ridotti e permette di essere applicabile anche in casi non sia possibile fare training o non sia possibile generare delle istanze forged, ma presenta prestazioni peggiori rispetto agli altri modelli all'aumentare del dataset disponibile (problema mitigato con l'approccio a elezione).

Conclusioni | Flowchart per guidare la scelta del modello

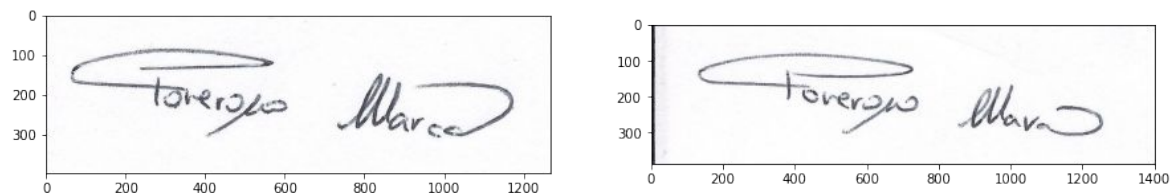


Esempio



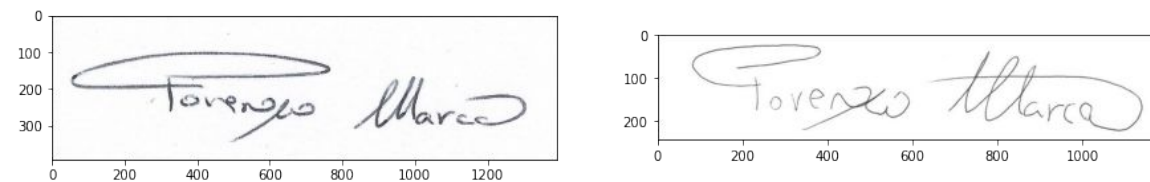
Come ultima prova abbiamo testato il modello con le nostre firme

COPPIA POSITIVA



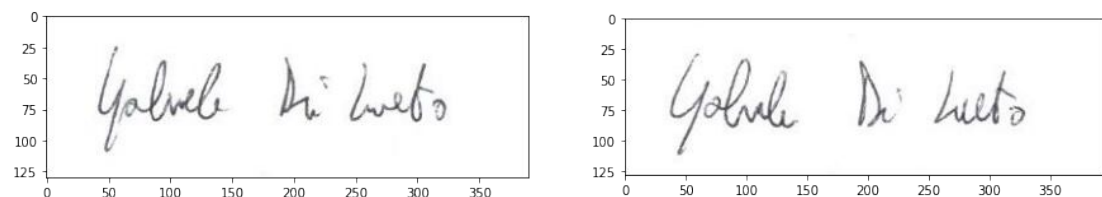
Similarità 0.78973215

COPPIA NEGATIVA



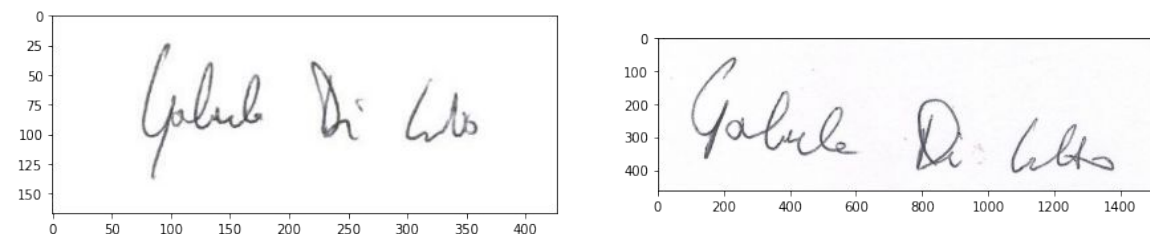
Similarità 0.01974825

COPPIA POSITIVA



Similarità 0.8332546

COPPIA NEGATIVA

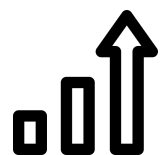


Similarità 0.01670848

Sviluppi futuri



Valutare l'applicabilità e le performance dei modelli per task simili (es. firma online, altri tipi di forgery).



Ottimizzazione la scelta delle ancore per i modelli writer independent.



Valutare i modelli sulla base di diverse necessità di performance (es. per avere una maggiore negative precision).



Valutare gli effetti di una pulizia più oculata dei dataset sulle performance di generalizzazione dei modelli (es. il problema della inter-class similiarity).



Grazie per l'attenzione