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A FRAMEWORK FOR INTELLIGENT DOCUMENT IMAGE ENHANCEMENT IN PURSUIT OF IMPROVED OCR PERFORMANCE

Ryno Kleinhans* Supervisor: Dr GS Nel



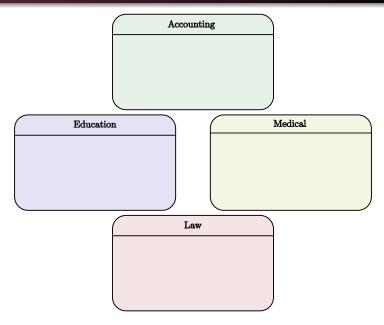
Stellenbosch Unit for Operations Research in Engineering Department of Industrial Engineering





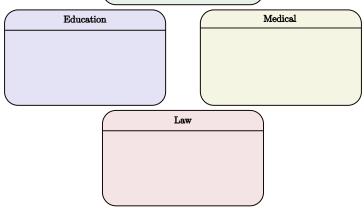






Accounting

- Single accountant prints 432 sheets of paper yearly
- $\bullet \; 0.57$ billion pages yearly (USA)
- Application forms, balance sheets, payslips, receipts



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- Single large hospital prints 96 million sheets of paper yearly
- 59 billion pages yearly (USA)
- Application forms, risk forms administrative documents

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- 59 billion pages yearly (USA)
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Law

- Single attorney prints 60 000 sheets of paper yearly
- 78 billion pages yearly (USA)
- Contracts, administrative documents, letters

Overview of the problem - Automation example



Overview of the problem - Text extraction phases

OCR definition

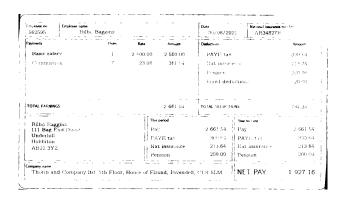
Optical character recognition (OCR) is the electronic conversion of pixel-based text data (i.e. a captured image) comprising typed, handwritten or printed text into machine-encoded text.



562595	Employee name Bilbo	Baggins			30/08/2023	National insurance AB34827F	
ayments		Units	Rate	Amount	Deductions		Amount
Basic sala	ary	1	2 500.00	2 500.00	PAYE tax		300.64
Commission		7	23.08	161.54	Nat insuran	ice	213.74
					Pension		200.00
					Fixed deduc	ctions	20.00
OTAL EARNIN	IGS			2 661.54	TOTAL DEDUCTION		734.38
Bilbo Baj	ggins			his period		Year to date	
Bilbo Baj	ggins End Street			his period	2 661.54 300.64		
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poloyee no. 562595 syments Basic sala Commissi	ry	Unites Rate	4	PAYE tax Nat insuran Pension Fixed deduc	24	300.64 213.74 200.00 20.00
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Company name Thorin and	Company Ite	5th Floor	House of Elr	ond, Rivendel	I, CD4 5LM	NET PAY	1 927.16



Informal problem description

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- ${\color{red} 2}$ Proposed framework walk-through

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- Real-world payslip case study

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- Receipt case study

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- Receipt case study
- Future work

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The principal aim in this research project is to design, develop and demonstrate the practical workability of a **generic framework** that introduces **machine intelligence** to the digitalisation of document images in order to **improve OCR performance**.

• Available data:

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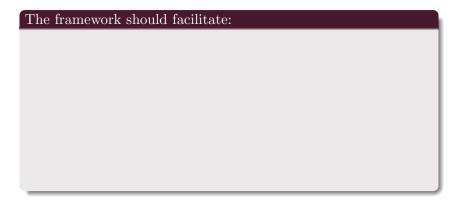
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 - Common document image enhancement techniques

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9/20

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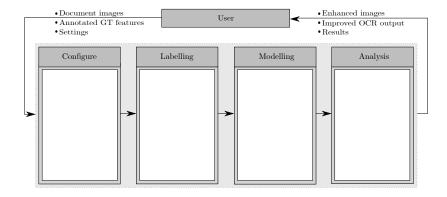
- The **preparation** of previously annotated data and its document images for analysis,
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- the prediction of the best enhancement procedure for each unique unseen document image,

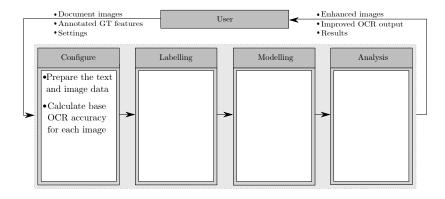
Document image enhancement

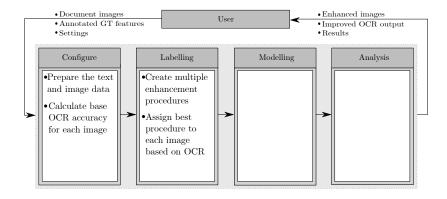
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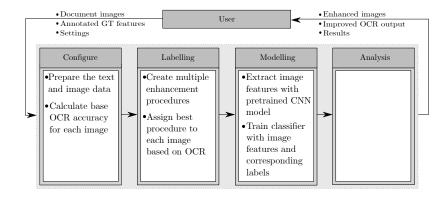
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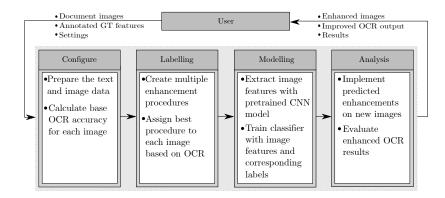
- The **preparation** of previously annotated data and its document images for analysis,
- the engineering and labelling of various unique enhancement procedures,
- the prediction of the best enhancement procedure for each unique unseen document image,
- **4** as well as the **implementation** and **analysis** of the predictions.





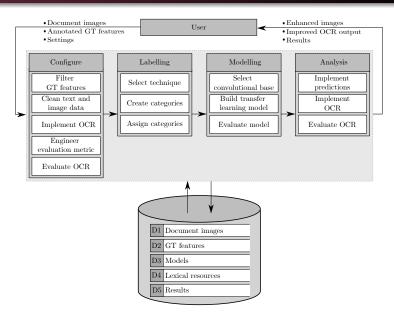






DOCUMENT IMAGE ENHANCEMENT

Proposed framework - Modules



 \bullet 2000 PDFs of scanned client payslips

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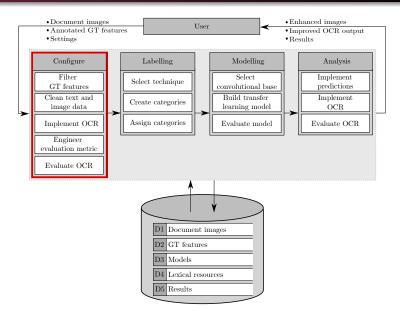


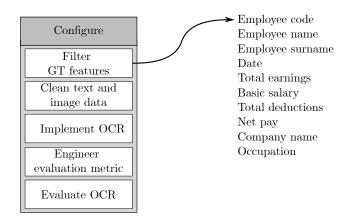


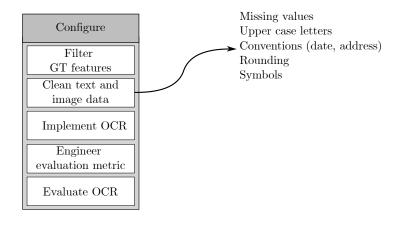


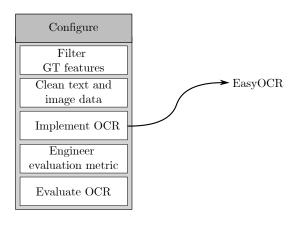


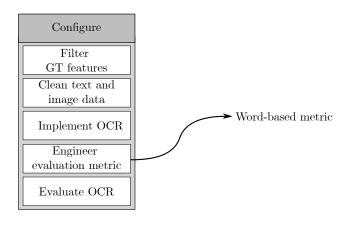


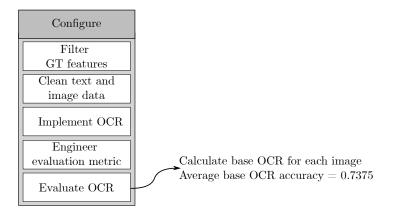


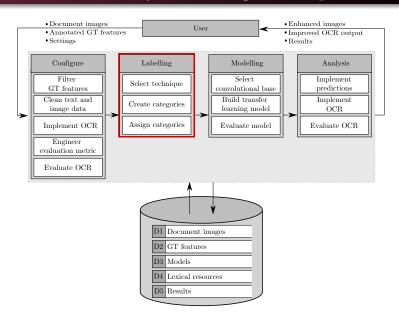


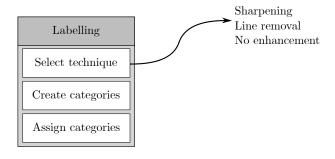


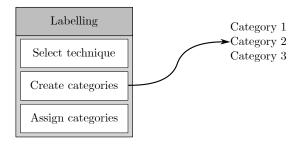


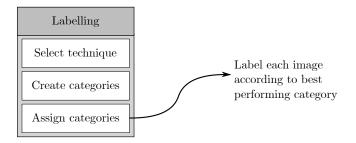


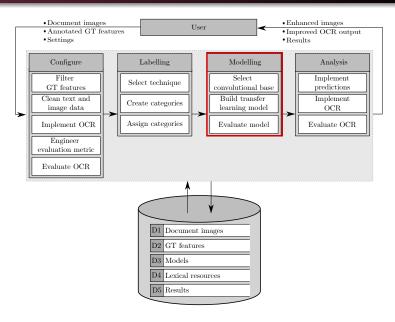


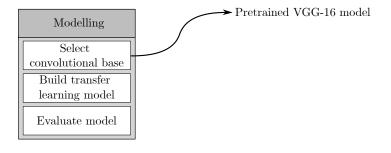


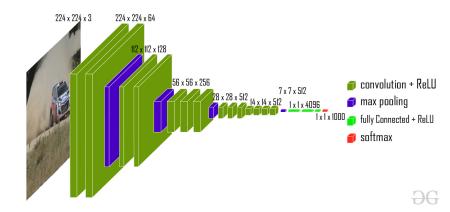


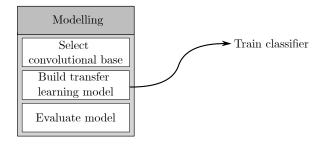


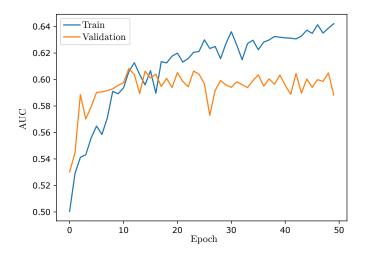


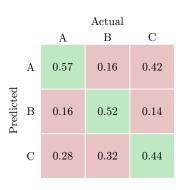








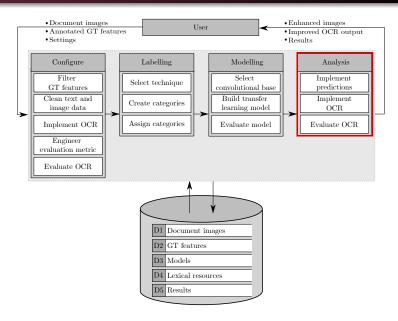




A: Base image

B: Line Removal

C: Sharpening



Test set category	Average OCR accuracy
Base	0.7382
Framework	0.7444

Impact category compared with the original base OCR	Line removal on all images		Sharpening on all images		Only predicted images	
	Number	Ratio	Number	Ratio	Number	Ratio
Improved	60	0.16	73	0.20	59	0.16
Same	249	0.68	187	0.51	268	0.73
Deteriorated	59	0.16	108	0.30	41	0.11
Improved/deteriorated		1.0169		0.6759		1.4390

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Case study 2 - Data provided by ICDAR

• 1000 PDFs of scanned restaurant receipts

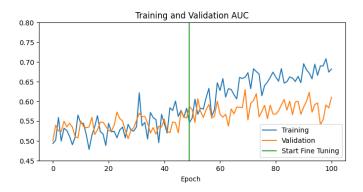
- 1000 PDFs of scanned restaurant receipts
- CSV with true values captured by annotators:

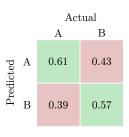
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Framework	0.7827

Impact category compared with the original base OCR	All images in test set		Only applied to predicted images in test set	
	Number	Ratio	Number	Ratio
Improved	38	0.30	22	0.18
Same	39	0.31	83	0.66
Deteriorated	48	0.38	20	0.16
Improved/deteriorated		0.7895		1.1250

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 - **3** applying the framework to document images with handwritten characters.

References



SMITH R, 2007, An overview of the Tesseract OCR engine, Ninth international conference on document analysis and recognition (ICDAR 2007), 2, pp. 629–633.



Jaided AI, 2020, EasyOCR, [Online], [Cited September 2021], Available from https://github.com/JaidedAI/EasyOCR