Final Year Project Report

**Full Unit – Final Report**

Solving Sudoku and Killer Sudoku Using AI

Manfred Sandy Alex Araujo

A report submitted in part fulfilment of the degree of

**BSc (Hons) in Computer Science**

**Supervisor:** Emma Lieu



Department of Computer Science

Royal Holloway, University of London

November 08, 2023

**Declaration**

This report has been prepared on the basis of my own work. Where other published and unpublished source materials have been used, these have been acknowledged.

Word Count:

Student Name: Manfred Sandy Alex Araujo

Date of Submission:

Signature:

Table of Contents

[Abstract 4](#_Toc150328183)

[Chapter 1: Introduction 5](#_Toc150328184)

[1.1 The Problem 5](#_Toc150328185)

[1.2 Aims and Goals 5](#_Toc150328186)

[1.3 Literary Survey 6](#_Toc150328187)

[Chapter 2: Constraint solvers 7](#_Toc150328188)

[2.1 Introduction 7](#_Toc150328189)

[2.2 Backtracking and Recursion 7](#_Toc150328190)

[2.3 Arc Consistency 7](#_Toc150328191)

[2.4 Back jumping 8](#_Toc150328192)

[2.5 Dynamic Variable/Value ordering 8](#_Toc150328193)

[2.6 Forward checking 9](#_Toc150328194)

[Chapter 3: Recursion and Backtracking 10](#_Toc150328195)

[3.1 Introduction 10](#_Toc150328196)

[3.2 First Sudoku Solver 10](#_Toc150328197)

[3.3 Improving the Solver 12](#_Toc150328198)

[3.4 Comparing the Sudoku solvers 13](#_Toc150328199)

[3.5 Killer Sudoku 14](#_Toc150328200)

[3.6 Comparing the Killer Sudoku solvers 15](#_Toc150328201)

[Chapter 4: Data Structures in Solvers 17](#_Toc150328202)

[4.1 Priority Queue 17](#_Toc150328203)

[4.2 Dictionaries and Sets 19](#_Toc150328204)

[Chapter 5: Machine Vision 20](#_Toc150328205)

[5.1 Grid extraction 20](#_Toc150328206)

[5.2 Straightening the Image 22](#_Toc150328207)

[5.3 Cell Extraction and Processing 23](#_Toc150328208)

[5.4 Machine Learning and Classification 24](#_Toc150328209)

[5.5 Killer Sudoku Machine Vision 24](#_Toc150328210)

[Chapter 6: Software Engineering 27](#_Toc150328211)

[6.1 Testing and UML diagrams 27](#_Toc150328212)

[6.2 Documentation 28](#_Toc150328213)

[Chapter 7: Bibliography 29](#_Toc150328214)

Abstract

Sudoku is a popular logic-based game that involves a 9 by 9 grid with some given numbers and the aim being to fill all the cells in the grid with the numbers 1 to 9. The rules of the game involve each row, column and box must use the numbers 1 to 9 exactly once. Killer Sudoku is a similar game to Sudoku but extends the game by adding "cages" around a group of cells that must add up to a specific number.

A case study in 2011 [3] shows that the mean time to solve a sudoku puzzle is between 8-23 minutes. This study was conducted using two web sources, the first was used by more expert puzzle solvers, and the second by a more varied skill range hence the difference in solving time. However, Helmut Simonis [4] describes sudoku as a constraint satisfaction problem using different propagation techniques to solve them within a few milliseconds. People are likely to find a sudoku or killer sudoku puzzle in places such as a newspaper or a magazine, where getting stuck on a solution usually means waiting until the next day to receive the answer. However, by using a solver, the puzzle could be solved in a few seconds and be shown to the user either directly or provide hints so the user can still get the satisfaction of solving the puzzle on their own. Along with the solver, using machine vision to upload puzzles and avoid the tedious nature of entering values manually is a strong motivation for working on this project. Additionally, the application will also have the feature to allow users to solve puzzles directly on the app meaning all the features will be in one convenient place.

Solving a Sudoku or Killer Sudoku puzzle involves using logic to fill cells as well as to remove possibilities from other cells. Both these types of puzzles use different deduction techniques such as Lone Ranger, elimination techniques, looking for twins and triplets in Sudoku as described by Lee Wei-Meng [1], and sum elimination, rule of k, and rule of necessity in killer Sudoku as described on killer sudoku online [2]. The techniques discussed in these sources are very important and they are essential to completing a Sudoku or killer Sudoku puzzle. However, the difficulty lies in the ability to spot where they can be used, this is where a solver can thrive and complete these types of puzzles incredibly quickly.

Since the rules of the game are so clear, the puzzle itself can be defined as a CSP (Constraint Satisfaction Problem). A CSP is a type of programming paradigm where the problem is represented as a model with the variables to be optimized, which in this case is each cell in the 9 by 9 2D array, the domain is defined which is between 1 to 9, and the constraint of the variable is that each number must appear only once in each 3 by 3 square, once in each column and once in each row. Constraint Solver tries to find a solution by assigning variables with values from their domain which satisfies all the constraints defined. If a value leads to a dead end, then backtracking is used to go back as described in [5]. One way to improve this approach would carefully choose which variable to try next, for example, using a priority queue to select a variable with the smallest number of possible domain values. This means that the search will fail earlier if the guess is not correct thus improving the speed at which a solution is found [6]. The main benefit of this approach is that it always guarantees that a solution is found as it tries all the valid numbers for each empty cell. Therefore, I am going to use a combination of backtracking, node consistency along forward checking to reduce the search.

# Introduction

## The Problem

Sudoku or killer sudoku puzzles are commonly found in places such as a newspaper or a magazine, with various levels of difficulty. Since they are available easily, they invite people with all levels of ability, but without the knowledge of solving them efficiently, it can lead to a frustrating end. Often the answer to the puzzle is not available straight away, for example, you may have to wait until the next day to find the solution. However, by using a solver, the puzzle could be solved in a few seconds [4] and can be used to compare solutions. In most cases, however, receiving the whole solution is not an ideal learning mechanism, instead providing hints or given solutions to a particular cell is more beneficial. Therefore, constraint propagation can be used to deduce how the solution to a cell was identified which can make people aware of the different techniques used to solve these problems. Another problem is that using a solver requires the user to enter the values for the Sudoku puzzle and cages for Killer Sudoku manually. This can be a tedious task and prone to error which can waste time and cause users to give up. The most practical solution to this problem is to use machine vision to allow the user to input an image of the puzzle and then convert the puzzle to a form with can be used by the solver.

## Aims and Goals

The first and main goal of the project is to create my solver for sudoku and killer sudoku so I can solve these types of puzzles incredibly quickly. I will research this topic and use techniques such as backtracking, value heuristics, and forward checking to create an efficient solver. I will first create a base solver with minimal efficiency techniques and then compare it with more efficient solvers. The final solver should be able to provide the user with an explanation on how the solution was achieve for example which technique was used. This will be used to write the report on what constraint solvers are the techniques involved and how the different solvers compare to each other. I will also write a separate report on human techniques for solving sudoku and killer sudoku problems.

The next milestone of the project is to create a machine vision algorithm that will allow users to upload images and then directly convert them into a 2D array. The purpose of this feature is to prevent the user from having to enter the values into the puzzle manually. There is also a sub-milestone where I will need to use machine learning to convert the number in the image to an integer which can be inserted into an array that represents the puzzle. Next, I can then pass the array to the solver and then generate a solution to the puzzle. I will also write a section on the report on what machine vision is and how I used OpenCV to build the algorithm.

Another milestone is to use the Django framework to create a website that will host the solver. I will create an interface to allow the user to play the game on the website as well as a feature that allows them to upload images of puzzles. The interface will be able to display to the user how a solution was found for a puzzle. Game playing will be a key feature of the interface, it will allow users to play the puzzles and supports common features such an taking notes, hints, and undoing actions. The purpose of setting up the application on a website is because they are very accessible and can be developed for any device with little code change. The interface should be simple, easy to use and have a minimalistic design, so the focus is on the intended features.

In addition, I will also generate my own sudoku and killer sudoku puzzles which can then be played on the website. I will try to generate puzzles of different difficulties so it can accommodate beginners to experts. I will also write a section in the report on how I was able to generate my puzzles and the algorithms I used to create them. As well as coding milestones, I will also have several more report milestones such as a section on the NP-hardness of sudoku and killer Sudoku as well as the time complexity of my solutions. Additionally, I will write reports on the data structures I have used to develop my application and the different software engineering processes I have used.

## Literary Survey

In the context of solving the Sudoku puzzle, CSPs are a widely used approach. One such approach [1] describes base backtracking which tries all possible values in the domain to find a solution. They also constraint propagation techniques such as arc consistency, forward checking, and value and variable ordering heuristics to improve the speed of the algorithm. This approach relies on the principle of “fail fast” described in [n] which tries to choose variables which have the smallest domains and hence failing quicker if the wrong value was assigned. This approach was built upon in [2] which carries out constraint programming but after each run if a conflict occurs it swaps the value which causes the conflict and carries on.

Machine vision is effectively used to allow a computer to see using a camera. One approach described in [9] is to extract a puzzle to process the image and use a machine learning model to detect if a puzzle is present in the image and find the edges of the puzzle. Another approach [10] is to avoid using machine learning and directly use the OpenCV library to filter out the noise in the image and try to detect the corners of the puzzle. After finding the edges of the grid the next step is to extract each cell and then use machine learning for number recognition which converts the image of the cell to a number. Techniques such as Multilayered Perceptron, Support Vector Machine, and Convoluted Neural Networks [11] are all useful methods used to recognize digits. This will improve the usability of the application as the user is not required to manually enter the values for the puzzle. However, it’s unlikely the model will have 100% accuracy therefore to account for the errors made the user can then manually replace values in the grid. Instead of using machine learning, another option is to use the tesseract engine which performs text recognition all by itself [2], this approach is widely used in the world for many tasks such as license plate detection. For my solution, I will mainly use [10] for the machine vision section as [9] requires an extensive dataset to be created from scratch which is not feasible. As for the number detection I will initially try using a machine learning model and if it performs badly, I will switch to the tesseract engine.

Another key area of my application is generating valid sudoku and killer sudoku puzzles, for a puzzle to be valid it must satisfy all the constraint of the puzzle but also only have one solution. One such approach to do this is described in [3], this method first gets a Sudoku grid which has all its cells filled, it then performs the inverse of known solving methods to remove a set number of values. Another approach described in [4] starts of again with a fully filled in grid, it then removes values one by on and checking if the puzzle is valid. This is done until the desired number of clues remain, this approach is a lot slower but always guarantees that a puzzle is valid. There are also more complex approaches such as using DNA computing as described in [5] which uses graphs and graphs colouring to generate puzzle. For my use case I am going to try to implement the method described in [4] which will highly depend on how fast my solver is and try to integrate [3] in cases of generating different difficulties of puzzles.

# Constraint solvers

## Introduction

Constraint Satisfaction Problems (CSPs) are a type of programming paradigm where the problem is modeled as a set of variables that we are trying to optimize, the domain space of the variable, and the constraints of the model [13]. They are very powerful for solving problems such as the N-queen problem, scheduling rosters, and playing games, where the goal is to find a solution where no constraints have been broken. Constraint programming (CP) tries to find the solution to these problems typically by a search algorithm and uses specific algorithms such as arc consistency, dynamic value ordering, forward check, and back jumping to increase its efficiency. Sudoku is one such problem that can be solved very efficiently using CPSs and in this section, I will write about the different algorithms which are used within CPSs.

## Backtracking and Recursion

Recursive backtracking is a type of algorithm that tries to find a solution to the problem by trying all possible values. It is usually implemented within a single function and is very easy and simple to build. In the case of Sudoku, the algorithm will get the first empty cell, assign it a value from its domain, and then call itself to fill the next empty cell. The backtracking part of this algorithm is what allows it to find solutions, if a constraint has been broken then the correct solution is wrong and will not lead to a correct solution. Therefore, the algorithm will backtrack to the last state in which the constraint was satisfied and try a different value.

def RecursiveBacktrack():

if isBrokenConstraint() == True

return False

if isComplete() == True:

return True

variable = getNextUnassignedVariable()

for value in variable.domain:

variable = value

if RecursiveBacktrack() == True:

return True

return False

The above code snippet shows the basic structure of a recursive backtracking algorithm. It backtracks if a constraint is broken, or no value leads to a solution and succeeds when the problem is complete. The benefit of this is that if a solution is possible, it will always find it. However, a major drawback is that it is highly inefficient since it may fail many times time until it finds the correct solution. For sudoku, there is a possible 6.6 × 1021 valid sudoku grid [14] and therefore trying every single value can take a very long time to complete making this algorithm very inefficient. In most cases the backtracking algorithm should not be used on its own, instead, the algorithm should be improved by adding other techniques such as arc consistency and dynamic value ordering.

## Arc Consistency

One way of improving the backtracking algorithm is using arc consistency. This algorithm does not solve the problem instead it tries to reduce the domain space for each variable. It is often described as a preprocessing step carried out before the search algorithm and its goal is to remove any inconsistent values from the domains [15]. In this case, inconsistency is defined as any value that does not lead to a solution, and by doing this, we can reduce the search space and therefore make the search algorithm faster.



Figure 1 – a row within a sudoku puzzle.

From Figure 1, you can see that the values 2, 1, 3, 6, and 4 already belong in the row. Enforcing arc consistency here would mean that the domain for the empty cells would not contain those values because they will never lead to a solution. Without arch consistency, the search algorithm would have included those values in the variable domains and ultimately failed resulting in significant wasted time.

## Back jumping

Backjumping is another algorithm that is used to make the standard backtracking algorithm faster. When we have reached a dead end, where a variable domain is empty, we usually backtrack in chronological order, but in backjumping, we backtrack directly to the variable assignment which causes the dead end to be reached [16]. By doing this we can avoid searching with a variable that will not lead to the correct solution and backtrack further to a safe state. Programmatically, during each recursive call the variable will have a conflict set that contains the variables that were involved in the conflict, the values assigned to those variables at the time, and the specific constraint that was broken. The conflict set tells us the conflict variable that is most responsible for the conflict and hence backtracks to change the value assigned to that variable and then resume the search. This way we have pruned the branches between the conflicted variable and the last variable and thus improved the speed of the algorithm.

## Dynamic Variable/Value ordering

Dynamic variable ordering is another concept within CSPs, and its main concern is the order in which the variables are processed. The idea is that if we carefully choose the next variable then we can “minimize the size of the search tree” [17] and prune a branch as quickly as possible if it is incorrect. This approach is also called Minimum Domain Size (MiD) which implements the “fail first” [5] approach. In this concept at every recursive call, we choose the variable with the smallest domain which reduces the number of branches compared to a variable with more options. Also, with a smaller domain, there is a higher probability that the chosen value will be correct for example if the domain of a cell is just 1 or 2 then there is a 50% chance that we are right on the first try. Dynamic Variable ordering can be implemented efficiently using a priority queue, we can first put all variables into the queue with their domain sizes to be ordered. Then when we make a recursive call, we choose the next value by popping from the queue.

Another approach which is like the DiM is Dynamic Value Ordering but instead of thinking about the variable to choose we look at the value to assign. The main idea is that if we choose the values carefully then we can increase the probability that the value we assigned is correct and reduce backtracking. There are many approaches such as a Smaller Value of the Domain (SVaL) and a Greater Value of the Domain (GVaL) where the heuristic chooses the smallest and largest value in the domain respectively [17]. However, in the case of sudoku, this doesn’t work but we can observe that each value 1-9 must appear exactly 9 times. Therefore, we can choose the value which is least used so far and the heuristic.

## Forward checking

Forward checking is an algorithm that is concerned with verifying and updating the domains of the related variables after assigning a value to a variable [18]. The main idea behind this algorithm is to reduce the domain of the variables and thus reduce the size of the search tree. For sudoku, after assigning a value to a variable we can implement forward checking by then removing that value from all other cells which are in the same row, column, and box. During this process, if any variable domain is empty then we know that the current assignment was wrong so we can immediately backtrack and prune the branch earlier. In addition, we can exclude a value that will lead to a conflict later and narrow down the search even more.

Def forwardCheck(current\_cell, assigned\_value):

For cell in relatedCells:

If assigned\_value in cell.domain:

cell.domain.remove(assign\_value)

If len(cell.domain) == 0:

Return “backtrack”

The above pseudocode describes an implementation of the forward checking algorithm which is called each time a value is assigned to a value. It loops over all the related cells and removes the assigned value if it exists in its domain. Then it checks if the domain for the cell is empty if it is then it triggers a backtrack.

# Recursion and Backtracking

## Introduction

The first task which I worked on was working on a solver for Sudoku which involved learning about constraint solvers and then onto the killer Sudoku solver. Many libraries are designed for constraint satisfaction problems such as python-constraints, CPMpy, Google OR-tools, and more. However, I wanted to create a solver from scratch without using a predefined library as it gave me more control over how I wanted the solver to work. First, I created a baseline model which used only backtracking and Consistency. Then I will try to create an improved model using value ordering heuristics to make the model faster by allowing incorrect branches to be pruned earlier.

## First Sudoku Solver

An important part of constraint solving is to identify the domains for the variables within the problem. I started by creating a getDomain method which takes a row and column and returns an array containing all the possible values it can contain. An obvious starting place for this would be to simply assign the numbers 1-9 to every cell and let the backtracking function deal with the incorrect values. However, I realized that this was not a good idea because some values would be guaranteed to not be correct so I could simply remove those values from the domain.

### Setting up a sudoku class

The first step to building the solver is to have a base class that will be used to represent the problem better. I started by defining a simple class called Sudoku and its constructor which simply accepts a 2D array. A zero in a slot represents that the cell is empty and if it contains a number between 1-9 then it contains a given hint. While this is the main behavior, I also decided to add an isValid method which checks whether a puzzle is valid. For a puzzle to be valid it needs to satisfy all the constraints such as each cell in a row, column, and box must be unique. Another requirement is that the puzzle must have exactly one solution, however, this cannot be implemented yet because it relies upon the solver being built.

    def checkBox(self, row, col):

        row = row \* 3

        col = col \* 3

        unique\_values = {}

*for* i *in* range(3):

*for* j *in* range(3):

*if* *self*.grid[row+i][col+j] != 0 and *self*.grid[row+i][col+j] in unique\_values:

*return* False

                unique\_values[*self*.grid[row+i][col+j]] = 1

*return* True

The above code snippet is used to if a box is valid, it does this by first identifying the cells involved in the box and then putting all the values into the dictionary as it sees them. If a new value Is already in the dictionary, it means there is a duplicate therefore the puzzle is invalid.

### Arc-consistency

Arc consistency is a constraint propagation technique used within constraint solvers to reduce the size of a domain by filtering out inconsistent values. In the case of Sudoku, an example of an inconsistent value would be any number that appears anywhere else in the cell row, column, or 3x3 box. This is because adding this number would not satisfy the Sudoku constraints defined. I implemented this technique by removing all the values within the cells domain which would violate the defined constraints.

   def getDomain(self, row, col):

        used = []

*for* i *in* range(9):

*#Get all values in the row*

*if* *self*.sudoku.grid[row][i] > 0:

                used.append(*self*.sudoku.grid[row][i])

*#Get all values in the column*

*if* *self*.sudoku.grid[i][col] > 0:

                used.append(*self*.sudoku.grid[i][col])

*#Get all values in the box*

        box\_row = (row // 3) \* 3

        col\_box = (col // 3) \* 3

*for* i *in* range(box\_row, box\_row + 3):

*for* j *in* range(col\_box, col\_box + 3):

                used.append(*self*.sudoku.grid[i][j])

*# getting all unique values*

        used = set(used)

*return* set([1,2,3,4,5,6,7,8,9]) - used

The above code listing the two for loops iterates through the given cells’ rows, columns, and boxes to get all the values that have already been used. It then simply returns all the values not within this set which are in the range one to nine. By using this approach, the domain space for a cell is decreased and we avoid trying values that were guaranteed to be incorrect and therefore improve the efficiency of the solver.

### Recursion and Backtracking

With the completion of the getDomain method, I can now work on the core part of any constraint solver which is the backtracking algorithm. The algorithm works by first getting a cell that doesn’t already contain a value and then assigning it a value from its domain and then recursively calling itself until every cell has a value. In the case that a cell has no value in its domain (due to an incorrect value being assigned to a variable earlier) the algorithm will backtrack and try another value.

    def solve(self):

        row, col = *self*.findNextEmpty()

*if* row is None:

*return* True

        domain = *self*.getDomain(row, col)

*for* value *in* domain:

*self*.sudoku.grid[row][col] = value

*if* *self*.solve():

*return* True

*self*. sudoku.grid[row][col] = 0

*return* False

The findNextEmpty method simply returns the first slot in the array which does not contain a 0 in it. If the method returns None it means that there are no more empty cells therefore the puzzle has been completed. The backtracking algorithm is usually the backbone of a constraint solver because while you may have other constraint propagation methods, they may not always find a solution. The benefit of backtracking is that it will always find a solution to a problem if the puzzle is valid. However, a problem of backtracking is that it is slow because it is using trial and error to find a solution and in the worst case it would have to try every value in the domains for all cells. Therefore, it is important to have other constraint propagation techniques (explained in a future section) to do most of the heavy lifting and use the backtracking algorithm.

## Improving the Solver

The solver can be made faster by carefully choosing the next cell to be assigned a value, currently, the algorithm simply chooses the first empty grid slot. However, we can do better by choosing the slot with the smallest domain space first. This strategy is often called the “fail-first” approach described by Haralick [5] and by choosing the cell with the smallest domain we can discard values that do not lead to a correct solution quicker. Also with a smaller domain, we have a higher probability that the value assigned is the correct one.

### Fail first value ordering heuristic.

To implement this strategy, I decided to implement a priority queue to store all the cells and their domain space in order of smallest domains first. Since I wanted the heap to be efficient, I adapted the code provided by the Python documentation [12] to implement the priority queue using the heapq library. Before running the backtracking algorithm I first need to instantiate the queue by giving it the domains for each empty cell.

    def setupHeap(self):

*for* i *in* range(9):

*for* j *in* range(9):

*if* *self*.sudoku.grid[i][j] == 0:

                    values = *self*.getDomain(i, j)

*self*.heap.addToHeap((len(values), (i,j), values))

In the code snippet, I show how the queue is instantiated and the reason why I store the actual domain values in the heap is so that we do not need to recompute the domain values each time. However, this approach means that we need to manually keep the domains for each cell up to date every time we guess a value for a cell. I will discuss the implementation of the queue in a later section.

Now with the queue set up, I no longer require the getNextCell method as I simply need to pop the first value in the heap to get the next best cell and assign it a value from its domain. After assigning a value all the cells in its row, column and box need their domains to be updated to remove the assigned value.

        removed = []

*for* i *in* cells:

*if* val in *self*.key\_map[i][3]:

                m\_set = *self*.key\_map[i][3]

                m\_set.remove(val)

                removed.append((i, val))

*self*.addToHeap((*self*.key\_map[i][0] - 1, i, m\_set))

*return* removed

In the above snippet, I check each related cell's domain and see if it contains the value assigned, if it does then I keep the original copy of the cell and its domain and push the updated copy into the queue. After processing all the cells, the array containing the original domains and cells is returned to the recursive frame. The reason why I store the original copy is that if the cell was assigned the wrong value, then we need to put the original domains back into the queue. So instead of recomputing the previous domains, I can simply put back the stored domains.

*for* updated *in* updatedCells:

            m\_set = *self*.key\_map[updated[0]][3]

            m\_set.add(updated[1])

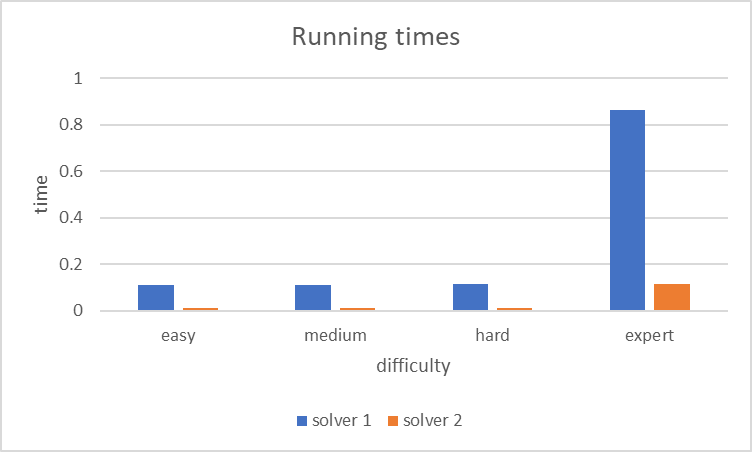
*self*.addToHeap((len(m\_set), updated[0], m\_set))

In the above code, the updatedCells variable is the array from the previous code snippet. So, we just put the removed values back into the domain and push it into the queue.

I can keep the updating of the queue efficient by keeping each cell in a dictionary as a key and its entry in the queue as the value. Therefore, locating the entry for a cell can be done in O(1) time. Also, instead of removing old domains from the queue, I can simply mark them to be ignored. While this means that the queue gets filled with old values, making the pop method less efficient, it makes removing values significantly quicker.

## Comparing the Sudoku solvers

In this section, I will compare the two different solvers have built and look at how they perform with different difficulties of puzzles.



1. Graph showing how the solvers perform on different puzzles.

In Figure 1 the bars for the easy, medium, and hard puzzles represent ten thousand runs of both the solvers. As for the expert puzzle it is built specifically to be as difficult as possible, and the graph shows just one run of the puzzle compared to the ten thousand runs of the other difficulties. From Figure 1 it’s very easy to see that the second solver with values ordering heuristics and forward checking is better than the first solver with just arc consistency. On average the second solver took around 0.01 seconds while the first solver took around 0.1 seconds so it's roughly 10 times better. Another interesting point is that the running time for the easy, medium, and hard puzzles took roughly the same time for the solver to complete whereas for humans as the puzzles get harder the time to complete would also get harder. However, while the solvers are fast, the expert puzzle shows that there is still room for improvement, this is because backtracking algorithms on their own are not very efficient.

## Killer Sudoku

My approach for the killer sudoku solver was very similar to the sudoku with some minor changes due to how the class was set up. I started by implementing a baseline solution which just used a backtracking algorithm and arc consistency, and then implemented a second version with dynamic value ordering and forward checking.

### Base class

My first step was to implement the killer sudoku base class which would hold the grid and the cages associated with it. For the grid, I used the 2D array and as for the cages I opted for a dictionary that had the cage number as keys and another dictionary as the value. The second dictionary had a key to the cage sum and the values of the cells in the cage. The reason I set the cages up like this is so that I had a way to quickly get all the cells in a particular cage. However, a problem was that given a cage it was difficult to get its cage number, so I implemented a method that went through the cages dictionary and instantiated another array with the key as the cell and the value as the cell cage number. With this, I was able to get all the information about a particular cell in O(1) time. I also created a method that checks whether the puzzle was valid, by simply checking if all cells were contained in a cage, all cage sums added to 405, and if the sudoku requirements were met.

### Backtracking algorithm

To implement arc consistency, I had to create a method to get the domains for the cells that will be used in the backtracking algorithm. The main part of the method was the same as the sudoku getDomain method however I needed to add some code to factor in the cage cells. Since a rule of killer sudoku is that there can be no duplicates with cages as well I added the following code to the method.

*for* i *in* cageCells:

*if* *self*.KSudoku.grid[i[0]][i[1]] != 0:

                cageSum = cageSum - *self*.KSudoku.grid[i[0]][i[1]]

                used.append(*self*.KSudoku.grid[i[0]][i[1]])

                count += 1

*if* cageSum <= 0:

*return* {}

*if* count == len(cageCells) - 1:

*if* cageSum > 9 or cageSum in set(used):

*return* {}

*return* {cageSum}

        used = set(used)

        validGuesses = set([1,2,3,4,5,6,7,8,9]) - used

        validGuesses = {i *for* i *in* validGuesses *if* i <= cageSum}

*return* validGuesses

In the above code first, I retrieve the cage number and then the cells in the cage, and next the for loop, add all the given values to the used array. Instead of just returning the numbers not in the used array as before, I added an extra check, if this was the last cell to be filled then there can only be one value which is the cage sum minus the other cage values. Then I can return the cage value if it is not present in the used array otherwise it returns an empty array which triggers a backtrack. Also, I added a condition that returned an empty array if the remaining sum of the cage was 0 or below because it meant there was no value in the 1-9 range which could get a 0 or below. The final task was to implement the backtracking algorithm, but this was a very easy task because the code was exactly as described for the first Sudoku solver. The only difference was the getDomain method as described above.

### Improved Solver

To improve the solver, I once again implemented dynamic variable ordering into the solver to decrease the size of the search tree. I used the same concept of the priority queue as described in section 2.3.1. While the concepts used were the same, they were implemented slightly differently, the difference was in the updating of the priority queue.

## Comparing the Killer Sudoku solvers

In this section, I will compare the two solvers I have implemented for killer Sudoku. For this section, I have used sudoku.com [19] to generate some puzzles with different difficulties and run the two solvers on them.

1. A graph showing the running time for the killer Sudoku solvers.

Figure 1 shows that both solvers are very quick at solving the easy puzzles with both completing the puzzles in 0.3 seconds. For the medium puzzle, the initial solver seems to perform better by about 5 seconds. One reason for this is that because I need to constantly update the priority queue after making a guess, the running time is increased. However, as shown above, the running time for the hard puzzle is significantly different, the second solver is about 12 minutes faster than the first. This clearly shows that the second solver performs significantly better on tougher puzzles while the first, does better on easier puzzles. One observation is that the killer Sudoku solvers are significantly slower than the Sudoku solver, that is because while Sudoku puzzles usually give a few prefilled cells, a killer Sudoku is empty. This means that the algorithm must fill the grid from scratch, as there are 6.6 × 1021 valid sudoku grids [14] and more for killer sudoku since there are many different cage arrangements meaning this can take a long time. Figure 1 demonstrates the need for a better solver because taking more than a minute would decrease interest in the application.

# Data Structures in Solvers

## Priority Queue

### Adding to the heap

The Constructor for the class initializes the following items:

*self*.pq = []

*self*.key\_map = {}

*self*.REMOVED = '<removed-task>'

*self*.counter = itertools.count()

The pq array represents the priority queue, which is implemented using the heapq python library, the key\_map dictionary is used to map the query entry, so accessing random elements in the queue can be done in O(1) time. The REMOVED variable is used as a placeholder for removed items and finally, the counter is used to rectify cases when the items have the same priority. With the code set up, I can implement the first method which is adding elements to the queue.

    def addToHeap(self, item):

*if* item[1] in *self*.key\_map:

*self*.remove\_cell(item)

        count = next(*self*.counter)

        entry = [item[0], count, item[1], item[2], "available"]

*self*.key\_map[item[1]] = entry

        heapq.heappush(*self*.pq, entry)

The method first checks if the cell entry already exists within the queue, if it doesn’t then we can simply push the element into the queue and save a pointer to the entry via the key\_map dictionary. If the cell is already in the queue, then we need to remove the item, so we only have one “active” entry per cell. Finally, an individual entry contains the priority of the entry which is represented by the length of the cell’s domain. The second element is the count which is a unique incrementing value. So, in cases where two cells have the same priority the cell pushed first has more priority. The third is the row and column of the cell, the fourth is the actual domain of the cell and finally, the string represents whether the elements are “active” or not. The reason why the actual domain is in the entry is so that we do not need to recalculate the domain of the cell each time, I can simply use the store values.

### Removing and popping items

When talking about items in the queue I referred to them as “active” or not in the last sections. This is because when I want to update an entry, instead of popping it and reordering the queue, we can simply ignore the element by giving the entry the REMOVED tag as defined in the constructor.

    def remove\_cell(self, task):

        entry = *self*.key\_map.pop(task[1])

        entry[-1] = *self*.REMOVED

The above code does exactly that it, simply finds the entry using the key\_map dictionary and changes the last element to the removed status. As for the pop method it simply uses the heappop method predefined in the heapq library.

    def pop\_cell(self):

*while* *self*.pq:

            priority, count, cell, domain, status = heapq.heappop(*self*.pq)

*if* status is not *self*.REMOVED:

*del* *self*.key\_map[cell]

*return* priority, cell, domain

*return* None, None, None

The while loop is needed so that we can keep popping entries until we get an entry that doesn’t contain the removed tag, hence ignoring the entry. If the entry is available, then we delete the mapping and return the cell, priority, and domain to be used by the solver. If the queue is empty, then we have successfully assigned a value to every cell and so return None for all, which internally signals the end of the solving algorithm and returns the completed grid.

### Updating the queue

After the solver makes a guess for a particular cell, all the cells within the row, column, box, and in killer Sudoku the cage needs to be updated. Also, in cases where we need to backtrack, the changes made previously need to be reverted so essentially re-update the affected cells. Since updating and reverting are going to be needed a lot, multiple times each recursive call, this needs to be efficient. The heapq library implements the priority queue using a binary heap internally, therefore removing random entries is very inefficient, so by using the available and removing tag we can simply ignore “removed” elements. The first part is updating the cell domains after a guess has been made:

*for* i *in* cells:

*if* val in *self*.key\_map[i][3]:

                m\_set = *self*.key\_map[i][3]

                m\_set.remove(val)

                removed.append((i, val))

*self*.addToHeap((*self*.key\_map[i][0] - 1, i, m\_set))

*return* removed

The above is a snippet of the decreaseKey method which updates cell entries. For the case of Sudoku and even non-cage cells in killer Sudoku, only one value is inconsistent, which is the value used when the guess was made. Therefore, instead of manually recalculating the domains every time we need to simply check if that value exists in the cells domain which is saved in its entry in the queue. If it does then we remove it and add a new entry for the cell in the queue, otherwise, we move on. At the end we return all the cells that were updated, this is important for the reverting stage.

When a backtrack occurs we need to revert the queue to the state before the last guess was made. By getting all the entries that were updated in the decreaseKey we can implement a simple method that just puts those entries back into the queue.

    def increase key(self, updatedCells):

*for* updated *in* updated cells:

            m\_set = *self*.key\_map[updated[0]][3]

            m\_set.add(updated[1])

*self*.addToHeap((len(m\_set), updated[0], m\_set))

The above code deals with the reverting of the queue, it takes all the entries that were changed previously and puts them back into the original state. By doing this, the previous action is undone, and the queue is kept consistent.

When updating cells that are part of the cage, we cannot simply remove the values guessed as is the case with non-cage cells. Instead, the domains change in a few ways but dealing with this manually is around the same as just recalculating the domain therefore that is the approach I went with.

## Dictionaries and Sets

When developing the solver there are many places where I have implemented a dictionary or a set. This is because they are very efficient and allow access to an element to be done in O(1) time, while they can be space inefficient, this is not a concern and I have prioritized the time complexity. The cages in my killer Sudoku class are implemented using a dictionary, this is a convenient way to store them and identify cages. However, finding which cage a cell belongs to and hence getting all its other cage cells is very inefficient. Therefore, I implemented another dictionary that maps each cell to its cage number, now I can get all information about the cages in O(1) time. This is important because the solver frequently needs to know which cells are grouped together and if implemented inefficiently then the running time could grow by a lot.

Sets are also a useful data structure that is used mainly when dealing with the domains of a cell. When checking if a domain contains an element, using sets is very useful because I do not need to loop through the set like an array. Instead, it uses hashing to check if the values exist within a set that is O(1) in time complexity.

# Machine Vision

The ability for humans to see is something that happens seamlessly without needing to deduce what it is that we are seeing. When looking at a tree, we just “know” it is a tree we do not need to process it, machine vision is the outcome of allowing computers to see [2]. A computer can see through images and videos but requires time to process the information and extract meaningful information from it. In this section, I will describe how machine vision was used to extract the sudoku and killer sudoku puzzles from an image and convert it to a form understood by the solver. The algorithms in this report are based on the algorithms described in [3].

## Grid extraction

The first task for the machine vision is to find and extract the puzzle from the image and hence work an image containing only necessary information. To do this we can take advantage of the signature thick borders of a Sudoku and killer Sudoku puzzle. However, before doing this we must convert the image the image to grayscale and apply a threshold that aims to reduce the noise in the image.

image = cv2.cvtColor(image, cv2.COLOR\_BGR2GRAY)

*# Applying adaptive threshold to the block*

threshold = cv2.adaptiveThreshold(image, 255,

cv2.ADAPTIVE\_THRESH\_GAUSSIAN\_C, cv2.THRESH\_BINARY, 91, 0)

The above code snippet first converts the image to a grayscale and then applies an adaptive threshold to remove the noise in the image. Thresholding works by looking at the neighbors of a pixel in this case 91 neighbors and finds the mean pixel value to be assigned. All values below a mean are set to 0 (white) or 255 (black) otherwise.

A square with numbers on it

Description automatically generatedA square puzzle with numbers and a square grid

Description automatically generated with medium confidence

Figure 2 – An image containing a Sudoku puzzle (Left) and the same image after applying the threshold (Right)

Now that the image is in the correct format, we must find all the contours which are contained. A contour is simply defined as the continuous border that encompasses an object, the border of the sudoku is a contour because of the outline that surrounds the puzzle. OpenCV provides a method findContours to do exactly this, however, because the image is still noisy it will final many contours as shown in figure 3 below.

A green square with black numbers on it

Description automatically generated

Figure 3 – the original image with all the edges drawn on it.

This problem can be solved by sorting all the contours by area and ignoring all the smaller contours. Looking carefully it can be seen that the meaningful contours such as those around the numbers, words, or the puzzle itself have a larger area. Through sorting we can then identify the contour which surrounds the puzzle by getting the second largest contour, this is because the largest will be the image border. This is one of the assumptions I am going to make because in most cases the puzzle may not be the second-largest contour, however, it makes the code significantly easier to write.

contours, hierarchy = cv2.findContours(image.copy(),

cv2.RETR\_TREE, cv2.CHAIN\_APPROX\_SIMPLE)

*# sorting the contours by areas*

cnt = sorted(contours, key=cv2.contourArea, reverse=True)

*# The second contour in the puzzle the first is the border of the image.*

puzzleContour = cnt[1]

The above code snippet shows how to find the contour that surrounds the puzzle. It first finds all the contours in the image, cv2.RETR\_TREE simply states to find all contours inside the image. Next, the contours are sorted through the sorted method and finally, we just take the second contour from the image to be the puzzle. Figure 4 is the final output which shows the image with its contours which contains the puzzle drawn on it.

A crossword puzzle with numbers and a green border

Description automatically generated

Figure 4 – the original image with the puzzle contour drawn on it.

## Straightening the Image

Before moving on to extracting each cell from the image the image must be straightened to avoid dealing with unnecessary information. As shown in Figure 4 the puzzle itself within the image does not form a perfect square, particularly on the left side, the line appears slightly tilted. We solve this problem by effectively stretching the image to fit inside a 450 by 450 box. To do this we first need to find the four corners of the contour, this is because the contour is simply comprised of a set of points, so we need to figure out which ones make up the corners.

To find the corner I used the Ramer-Douglas-Peucker algorithm [4] which recursively tries to remove points within the contour if they are not within a set parameter distance apart to get a smoother contour. Since the puzzle has four corners and are straight lines the algorithm will remove all contours in between the corners and give exactly the four corners of the puzzle. Now that we have the corners we can stretch or shrink the puzzle to fit within our set box.

def straightenImage(self, processedImage, edges):

*# Creating a 450 by 450 template image*

        dst = np.array([[0, 0], [450, 0], [450, 450], [0, 450]],

dtype='float32')

*# Calculate the perspective transformation matrix*

        M = cv2.getPerspectiveTransform(edgePoints, dst)

*# Apply the perspective transformation to the image*

        output = cv2.warpPerspective(processedImage, M, (450, 450))

*return* output.

The above code snippet is used to convert the puzzle into a perfect square. It starts by creating a canvas for the final image which is 450 x 450 pixels. Next, the getPerspectiveTransform uses the corner points of the contour and the target canvas to create a matrix M which is a transformation of the puzzle to fit within the canvas. Finally, warpPerspective performs the transformation of the image giving us the final image which is shown in Figure 5.

A square grid with numbers

Description automatically generated

Figure 5 – The puzzle after applying the Ramer-Douglas-Peucker algorithm.

## Cell Extraction and Processing

Now that we have an of just the puzzle and is fitted within a 450 by 450-pixel image, the next step is to extract the individual cell within the image. The reason that I wanted the image to be fitted perfectly within a 450 by 450 image was so I could simply divide the image into 50 by 50 blocks. Due to Sudoku and killer Sudoku being 9 by 9, each 50 by 50 block will give us each cell within the puzzle.

    def CellExtraction(self, image):

*# defining the height and width for each cell*

        cell\_height = 450 // 9

        cell\_width = 450 // 9

        cells = []

*# looping through each cell in the image.*

*for* y *in* range(0, 450, cell\_height):

*for* x *in* range(0, 450, cell\_width):

*# getting each 50x50 block from the image*

                block = image[y:y+cell\_height, x:x+cell\_width]

*# Appending the extracted block to the cell array*

                cells.append(block)

*return* cells

The code snippet above is a simple algorithm that loops through every 90 by 90 blocks, extracts it, and appends it to an array. At the end, the cells array will contain all the 81 blocks that capture each cell in the puzzle. The next step is to identify which cell contains an integer in it and which does not. To do this effectively, I made another assumption which is that the integer must be in the center of the cell not touching the edges, and would have a width of more than half the cell height.



Figure 6 – the individual images after extracting.

  digit\_Cells = []

        contours, \_ = cv2.findContours(image, cv2.RETR\_TREE,

cv2.CHAIN\_APPROX\_SIMPLE)

*# Only process cells with more than one contour.*

*if* len(contours) > 1:

            cnt = sorted(contours, key=cv2.contourArea, reverse=True)

*# check if the contour is centered and the right size for a*

*digit.*

            x, y, w, h = cv2.boundingRect(cnt[1])

*if* h >= 46 // 2 and *self*.isCentered(x, y, w, h) == True:

                digit\_Cells.append(image[y:y + h, x:x + w])

*else*:

                digit\_Cells.append(-1)

*else*:

            digit\_Cells.append(-1)

The above code snippet above tries to code the assumptions I made earlier. It starts by finding all the contours of the image if there are none then we can be confident that no integer exists in the image. Otherwise, we check whether the biggest contour is of the correct dimension and centred if it is then we can assume it is an integer. If an integer has been found in a cell, it needs to be extracted from the image which is performed by converting the contour into a rectangle and using list slicing to remove and extract the integer. Figure 6 shows the images of the numbers after being extracted. Now these images of integers can be put into a machine learning model to classify and finally convert to an array.

## Machine Learning and Classification

The final step is to convert the images of integers found into the corresponding integer which can be done through machine learning. As described in [5] for number classification a CNN (convoluted neural network) performs the best, therefore I will use A CNN on the MNIST handwritten dataset.

# Setting up the model

model = Sequential()

# Adding a convolutional layer

model.add(Conv2D(32, kernel\_size=(3, 3), activation='relu', input\_shape=(28, 28, 1)))

# Adding a max-pooling layer

model.add(MaxPooling2D(pool\_size=(2, 2)))

# Flatten the output to get it in one dimension

model.add(Flatten())

# Adding dense layers

model.add(Dense(512, activation='relu', input\_shape=(28, 28, 1)))

model.add(Dense(10, activation='softmax'))

The above code snippet is my neural network which is a sequential model that simply adds each layer one by one. The first layer is the Conv2D which uses 32 filters to scan the images and extract specific features such as edges, shapes, etc. The second layer is the MaxPooling2D is used to make the image smaller to discard irrelevant information, for every 2 by 2 block I will replace the block with the max value. The third layer flattens the image into a 1D image which is a necessary input to the next layer. The final 2 layers are dense, and their role is to determine the probability of the image being each number, the integer with the highest probability is the classification. This model works very well as it gave me a test accuracy rate of 98.64% which is good enough for this purpose.

Finally, I can use the model to convert the image to their corresponding integers, I simply loop through the digit\_cells array and if an index has a -1 then it doesn’t contain an integer, so I place a 0 otherwise I pass the image to the CNN and replace the image with its prediction. With this, I now have the final array which contains the translation of the original image containing a puzzle to a 2D array that represents it.

## Killer Sudoku Machine Vision

In the case of Machine vision for killer Sudoku, the same steps apply up to and including the cell extraction. However, the next steps differ because of the way that the puzzle is laid out. Figure 7 shows the extracted cell from the Killer Sudoku. The next step is to find out which sides the cages are on and the cage sums.

A black square with a number

Description automatically generatedA black and white square with dots

Description automatically generatedA black and white square with a number

Description automatically generated

Figure 7 – Extracted cells from killer Sudoku.

The first part is to get the cage sums, this works largely the same as the Sudoku but instead of the integers being in the centre they are in the top left. Therefore, we can simply extract the top left of the cell and extract the digits as before. The other difference is that instead of single digits there can be multiple digits, however, this does not change much.

*if* w \* h > 80 and w \* h < 1500 and  h < 40 and w < 40:

*if* len(sums) == 0:

                    sums.append(canvas)

                    current\_x = x

*else*:

*if* x < current\_x:

                        sums.insert(0, canvas)

*else*:

                        sums.append(canvas)

Above is the code snippet for identifying integers, since there can be more than one integer, we get all the contours and check whether the area of the contours is within the specified bound and the width and height have a minimum value. If the condition is met then the digit is stored to be classified.

For finding the cages we can once again use the contours to figure out where the cages are located. From Figure 7 the cages are represented by a dashed line and using findContours in the OpenCV library each segment is a contour. Therefore, we can simply count where all the contours are located and that is where the cages are.

*if* center\_x < margin and x > 0:

                sides[0] += 1

*elif* center\_x > 110 - margin and x + w < 110:

                sides[2] += 1

*if* center\_y < margin and y > 0:

                sides[3] += 1

*elif* center\_y > 110 - margin and y + h < 110:

                sides[1] += 1

This code snippet is used to count all the contours and where they appear, the margin is simply 20 pixels from the edges and represents the side of the cell. After counting the contours if any side is greater than 5 then we can consider it a side otherwise it is not. I chose 5 due to potential noise and in most cases, the side has 8 contours, and hence a reasonable value. I can then arrange each cell as an array that contains whether it contains a sum, which side has cages 1 means has a cage on that side and 0 means it does not, and finally a checked variable.

    def constructCage(self, i, j):

        cageCells = [(i, j)]

        cell = *self*.cages[i][j]

*if* cell[5] == 1:

*return* []

*self*.cages[i][j][5] = 1

*if* cell[2] == 0:

            cageCells = cageCells + *self*.constructCage(i+1, j)

*if* cell[3] == 0:

            cageCells = cageCells + *self*.constructCage(i, j+1)

*if* cell[1] == 0:

            cageCells = cageCells + *self*.constructCage(i, j-1)

*return* cageCells

The above code snippet is a recursive algorithm that is called for all unchecked cells. If it is not checked it navigates through the cell and calls itself with the next open cell if there is one, if there’s no open cell then we have explored all open cells and so found all cells in the cage. At the end, each call will return a list of all the cells which are in the same cells. Finally, we have the grid and the cages with cage sums so, it can be passed to the killer sudoku solver to be solved.

# Software Engineering

## Testing and UML diagrams

A diagram of a company

Description automatically generatedOne of the most important parts of software engineering is testing and it is something I paid a lot of attention towards. TTD (Test Driven Development) was used for most of the backend code excluding the machine vision code. The machine vision code cannot be tested through automated tests as they are dealing with image processing, therefore I performed manual testing to make sure that it all worked. I have also performed some integration testing to make sure that the methods work as intended when run sequentially. As for the front end, I have used selenium to perform tests. I have used Selenium because it works well with plain HTML, JavaScript, and CSS. While it can be slow to run it can still test all aspects of the frontend such as the HTML elements, CSS, and even the backend interactions. Therefore, I have used it to test that all elements are displayed correctly as well as testing that the JavaScript code is interacting with the backend as expected.

Figure 8 – A UML diagram for the main puzzle solving code.

I have also made sure to plan out the general idea of the application through UML diagrams. Figure 8 is one of the UML diagrams I created, and it represents the main structure of the puzzle-solving code. It includes the class names, methods, class variables, and how the different classes are related.

## Documentation

I used GitLab to keep my project centralized and to avoid losing access to any of my work. I made sure to use feature branches to develop individual features and keep different development lines separate from each other. By using feature branches the main branch can be kept clean and always in a working state. I made sure to push all work to the repository and added a commit that provided essential information about the commit such as what changes were made and why.

To improve the readability of my code I have made sure to include appropriate documentation. I have used Pydocs to explain the role of methods and classes and their parameters and return items. In addition, comments have been placed throughout the application to increase the understanding of what the code is doing, especially in complex methods.

# Conclusion

The main objective of this project was to create a solver that could solve Sudoku and killer Sudoku puzzles using AI. As described in Chapter 3, I have mostly accomplished this, as the solver can give correct solutions for any puzzle, and in the case of Sudoku and the easier killer Sudoku puzzle, it can find solutions relatively quickly. however, there are many improvements I need to make in the future. I have learned about constraint programming and how it can be optimized to solve many types of problems efficiently such as forward checking, arc consistency, and more. However, my solvers can still be improved one way is to create a new solver that doesn’t use recursion as much, this is because recursive algorithms are slow especially as shown in the running time for the killer Sudoku for harder puzzles. One other requirement I had for the solver was to be able to give hints as to how a solution was reached, the current solvers do not do this. Therefore, In the new solver, I will implement human-solving Sudoku and killer Sudoku algorithms to logically find solutions, which in turn will rely less on a recursive algorithm.

The next objective I stated, was to implement a machine vision model which would allow users to enter puzzles through images and return the solutions. I have described in Chapter 5, my implementation for this, and it works well. However, the solution relies on a few assumptions to be made which unfortunately is unavoidable. The algorithm successfully extracts puzzles from the images and converts them to a human-readable form. One area the algorithm needs to improve in is the digit algorithm, while the machine learning algorithm has a success rate of 98% on the test data, it seems to struggle when it comes to classifying my data. This causes a lot of misclassification and hence requires the user to manually change the number more often. In the second semester, I will aim to find the solution to this problem and reduce the error rate of my algorithm.

While I have accomplished a good amount of my initial milestones, there is still a lot of work to be done in the second semester. The focus will be to improve upon the current application and the new features. The first feature to be added is an algorithm to generate my puzzle with various levels of difficulty. I have already researched this topic and have a general idea of how I could implement this. Another task will be to fully complete the frontend application, it currently supports the machine vision code and the puzzle-solving feature. However, it cannot generate its puzzle and has a puzzle hardcoded. Another feature to be introduced is the ability to store incomplete puzzles, while this can be accomplished using a database, I believe storing the data in the user’s local storage makes more sense and removes the need for the user to create an account. Finally, as stated earlier, I will improve upon the solvers to be faster to provide meaningful hints to the user and to improve the machine vision to give more accurate responses.

# Bibliography

|  |  |
| --- | --- |
| [1] | Brailsford, Sally C., Chris N. Potts, and Barbara M. Smith, “Constraint satisfaction problems: Algorithms and applications.,” *European journal of operational research,* vol. 119.3, pp. 557-581, 1999. |
| [2] | Čakić, Stevan, et al., “The use of tesseract ocr number recognition for food tracking and tracing.,” in *24th International Conference on Information Technology (IT). IEEE*, 2020. |
| [3] | Team #2306, “Generating Sudoku Puzzles as an Inverse Problem,” University of Washington, Washington, 2008. |
| [4] | “Sudoku Generator Algorithm,” 101 Computing, 21 3 2019. [Online]. Available: https://www.101computing.net/sudoku-generator-algorithm/. [Accessed 2023 11 08]. |
| [5] | Sudha, V., and R. Kalaiselvi, “The Sudoku Puzzle Generator Using DNA Computing.,” in *International Conference on Computational Intelligence, Security and Internet of Things. Cham: Springer International Publishing*, 2020. |
| [6] | Davies, E. Roy, Machine vision: theory, algorithms, practicalities, Elsevier, 2004. |
| [7] | K. Gupta, S. Khatri and M. H. Khan, “A Novel Automated Solver for Sudoku Images,” in *2019 IEEE 5th International Conference for Convergence in Technology (I2CT)*, Bombay, India, 2019. |
| [8] | Wikipedia, “Ramer–Douglas–Peucker algorithm,” Wikipedia, [Online]. Available: https://en.wikipedia.org/wiki/Ramer%E2%80%93Douglas%E2%80%93Peucker\_algorithm. [Accessed 06 11 2023]. |
| [9] | Ritik D, Rishika K, Samay P, “Handwritten Digit Recognition using Machine and Deep Learning Algorithms,” 2021. |
| [10] | W.-M. Lee, “Basic Sudoku Solving Techniques / Intermediate Techniques / Advanced Techniques,” in *Programming Sudoku*, Apress, 2006, pp. 47-171. |
| [11] | “Tips,” Killer Sudoku, [Online]. Available: https://www.killersudokuonline.com/tips.html. [Accessed 24 9 2023]. |
| [12] | Simonis, Helmut, *Sudoku as a constraint problem,* CP Workshop on modeling and reformulating Constraint Satisfaction Problems. Vol. 12. Citeseer,, 2005. |
| [13] | Simha, Pramod J., K. V. Suraj, and Tejas Ahobala, “Recognition of numbers and position using image processing techniques for solving sudoku puzzles,” in *IEEE-international conference on advances in engineering, science and management (ICAESM-2012). IEEE*, 2012. |
| [14] | R. Haralick and G. Elliot, “Increasing tree search efficiency for constraint satisfaction problems.,” in *Artificial Intelligence*, 1980, pp. 14:263-313. |
| [15] | Pelánek, Radek, *Human problem solving: Sudoku case study.,* Faculty of Informatics, Masaryk University, 2011. |
| [16] | “Django documentation,” Django, [Online]. Available: https://docs.djangoproject.com/en/4.2/. [Accessed 01 10 2023]. |
| [17] | Merugu Suresh, Azhar Talha Syed, “Augmented Reality on Sudoku Puzzle Using Computer Vision and Deep Learning,” in *Advances in Cybernetics, Cognition, and Machine Learning for Communication Technologies* , 2020, pp. 567-578. |
| [18] | Sun, B., Sun, X., Wu, Y., Yin, Y., & Yang, G., “A New Algorithm for Generating Unique-Solution Sudoku,” in *In 2008 Fourth International Conference on Natural Computation (Vol. 7, pp. 215-217).*, 2008. |
| [19] | “Heap queue algorithm,” Python, [Online]. Available: https://docs.python.org/2/library/heapq.html#priority-queue-implementation-notes. [Accessed 13 10 2023]. |
| [20] | Brailsford, Sally C., Chris N. Potts, and Barbara M. Smith., “European journal of operational research,” *"Constraint satisfaction problems: Algorithms and applications.",* vol. 119, no. 3, pp. 557-581, 1999. |
| [21] | Bertram Felgenhauer and Frazer Jarvis., “Enumerating possible Sudoku grids,” University of Sheffield, 2005. |
| [22] | Bessiere, Christian., “Arc-consistency in dynamic constraint satisfaction problems.,” in *AAAI Conference on Artificial Intelligence*, Anaheim, 1991. |
| [23] | Dechter, Rina., “Enhancement schemes for constraint processing: Backjumping, learning, and cutset decomposition,” *Artificial Intelligence,* pp. 273-312, 1990. |
| [24] | Crawford, Broderick, Carlos Castro, and Eric Monfroy., “Solving sudoku with constraint programming.,” in *Cutting-Edge Research Topics on Multiple Criteria Decision Making: 20th International Conference*, Chengdu/Jiuzhaigou, 2009. |
| [25] | Cazenave, Tristan, and I. A. Labo., *A search based sudoku solver.,* Labo IA Dept. Informatique Universite Paris 8, 2006. |
| [26] | “killer,” EasyBrain, [Online]. Available: https://sudoku.com/killer. [Accessed 2023 10 22]. |