YOUNGER

PREDICTING AGE
WITH DEEP LEARNING

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Executive Summary

- **Problem:** to develop and evaluate image-based supervised models to predict the age of the person in a given image, using deep neural nets.
- **Hypothetical Stakeholder:** A beauty company, ‘Younger’, requested an age predictor app to demonstrate the value of their ‘age-defying’ product line.
- **Results:** Using a customized Convolutional Neural Network (CNN) and Transfer Learning, we were able to estimate a subject’s age from a photograph with an average error of about 7 years.

```
Predicted Age:  64
------------------
Actual Age:     63
```

The Code

- All project code is available on my Github repository: **https://github.com/premonish/YOUNGER**
- The project was developed in Python using appropriate libraries on Google Colab Pro to take advantage of fast GPU-based architecture.
- TensorFlow and Keras were used for preprocessing and implementing the Convolutional Neural Network (CNN).

YOUNGER: GITHUB

The Dataset

- The dataset, *"IMDB-WIKI - 500k+ face images With Age and Gender Labels,"* related to this paper, is available for download for academic research only.
  https://data.vision.ee.ethz.ch/cvl/rrothe/imdb-wiki/
  - Created from scraped images from *IMDb* and *Wikipedia* of famous people
  - Massive public dataset of people's faces labeled with ages and gender
  - Images are centered and cropped

Photos from "IMDB-WIKI" Dataset

Practical Age Prediction

- **Marketing Applications**

  Ex: *Quividi* uses interactive signage which plays a specific ad/video based on age and gender

- **Law Enforcement**

  Estimating age to create a suspect profile

- **Access Control**

  Prevent underage access to prohibited materials – alcohol, nightclubs, cars, curfew enforcement, etc.

Photo by Milan Malkomes on Unsplash

Challenges

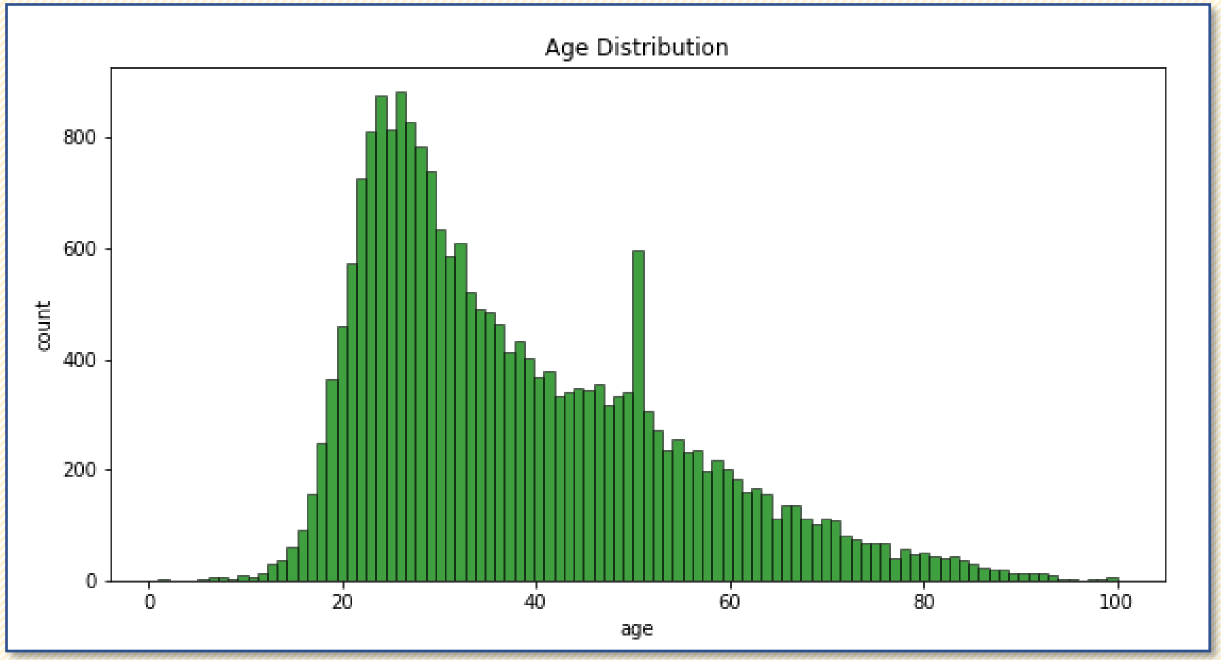
Many factors affect apparent age including:

- Makeup
- Photo resolution
- Photo processing (Filters)
- Camera Angle
- Lighting
- Expression
- Lifestyle:
  - Smoking, drinking, sun exposure, etc.

Photo by Persnickety Prints on Unsplash

Dataset Challenges

- Dataset is imbalanced.
- Ages 0-7 and ages 81-100 are underrepresented .
- We will focus on predicting for ages 8-80 only.
- In the future, we can collect more data for underrepresented age classes.



‘Average Face’ Images

Image 3. *Average of 1000 Female Images.*

Image 4. *Average of 1000 Male Images.*

Image 5. *Average of Age 60–69 Images.*

To explore the dataset, we created composite images ‘averaging’ the pixel values across various subsets: 1,000 females, 1,000 males, and all images from age 60-69.

Convolutional Neural Networks

CNNs can achieve state-of-the-art results in image classification.

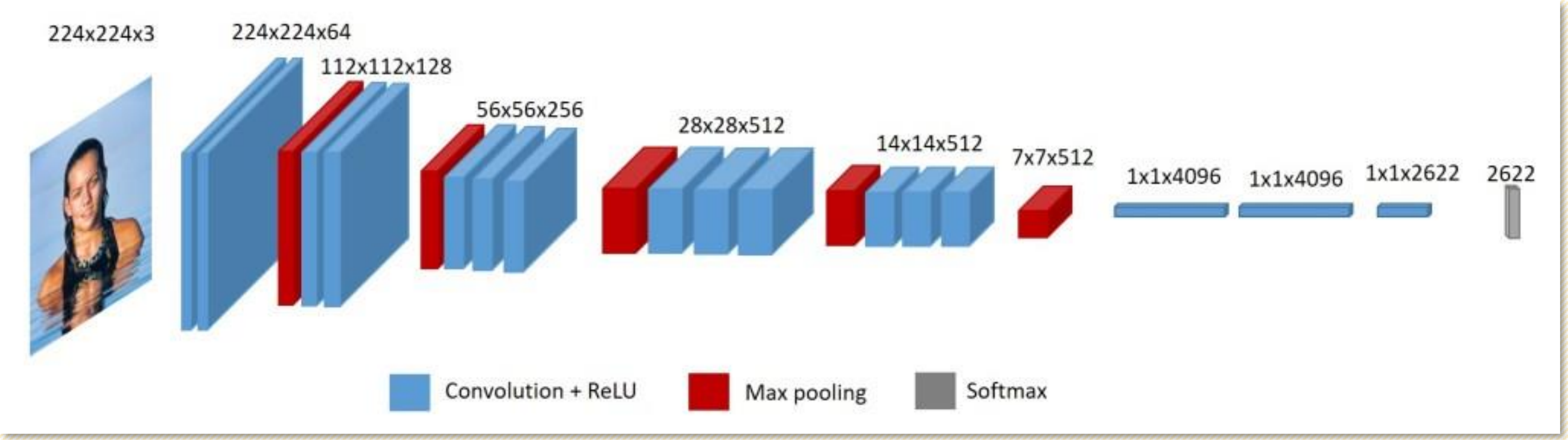
- Modeled on the biological visual cortex of animals
- Multi-layered feature extraction
- Enhanced by large datasets, and GPU computing
- Convolution uses matrix multiplication against a filter for feature extraction.
- Transfer Learning can expedite related tasks.

Photo by Vincent Ledvina on Unsplash

Convolutional Neural Networks

VGG-Face CNN Architecture

- Created for face identity recognition by Oxford's Visual Geometry Group (VGG)
- Can identify 2,622 faces
- Transfer Learning is possible since the task of age prediction has similar lower-level features (eyes, mouths, noses, head shapes, etc.).



VGG-Face Architecture Overview

Source: https://sefiks.com/2018/08/06/deep-face-recognition-with-keras/

Performance Metrics

- **MAE** – *Mean Absolute Error* – De facto performance metric for age prediction in literature
- **MAPE** – Mean Absolute Percentage Error
- **Test Set Classification Accuracy**
- **Test Set Classification Loss**

  (categorical cross entropy)

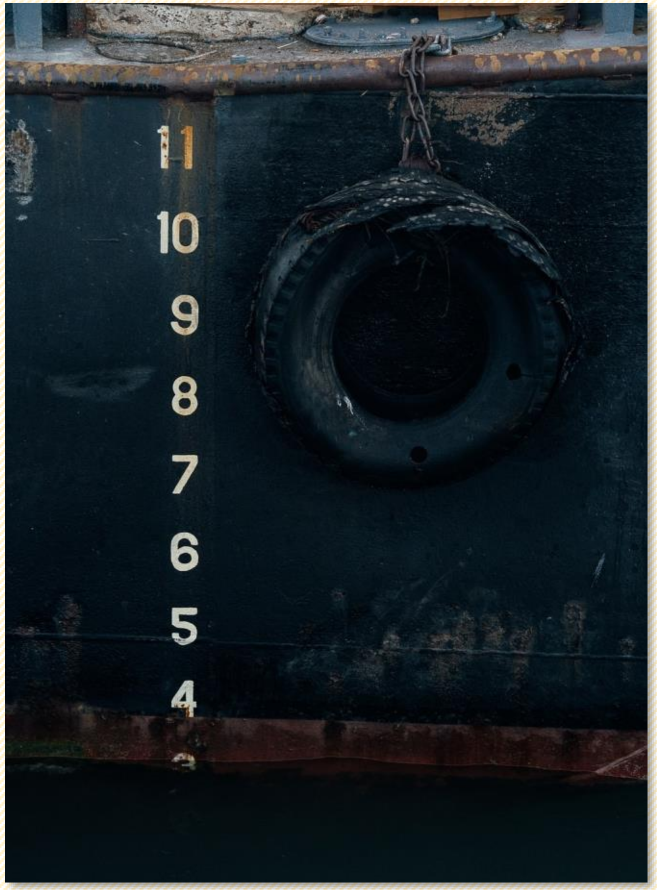


Photo by Thom Milkovic on Unsplash

Model Constants

Fix constants for model comparison:

- **Epochs** = 200
- **Batch Size** = 128
- **Training Set** = 3,525
- **Test Set** = 1,512
- **Training Set** : **Test Set Ratio** = 70:30

Photo by Julius Drost on Unsplash

Model Overview

- **CNN 1** = VGG-Face 'out of the box' with SGD optimizer
- **CNN 2** = VGG-Face with Adam optimizer
- **CNN 3** = VGG-Face with Adam optimizer with pretrained weights
- **CNN 4** = VGG-Face with Adam optimizer with pretrained weights & data augmentation

Photo by Clarisse Croset on Unsplash

CNN 1 - Baseline Model

- **CNN 1** = VGG-Face 'out of the box' with SGD optimizer

Observations

- The Baseline model has an MAE of 11.22, MAPE of 44.43%, Test Set Accuracy of 4.69%, and Test Set Loss of 3.92303.
- We can observe the training set diverge from the validation set on accuracy and loss, possibly indicating **overfitting**.

Fig 1. CNN1 Training Set / Test Set Loss

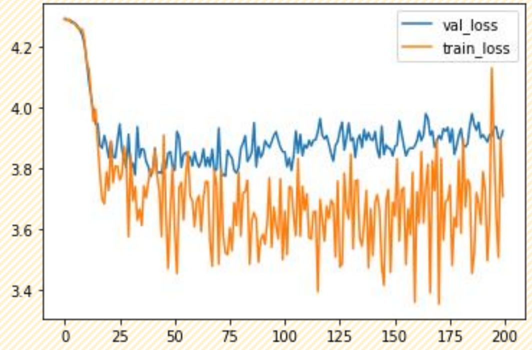
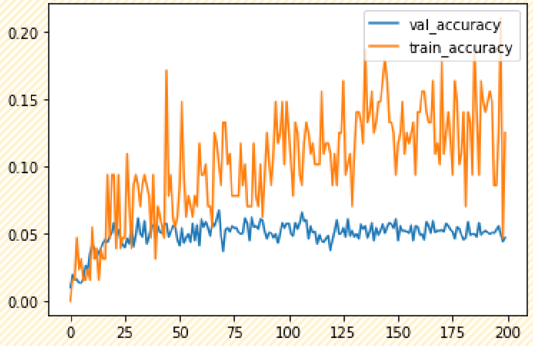


Fig 2. CNN1 Training Set / Test Set Accuracy



Test Set Model Performance Metrics				
	MAE	**MAPE**	**Test Accuracy**	**Test Loss**
CNN 1	11.22	44.43%	0.04696	3.92303
CNN 2	7.94	25.50%	0.08466	4.31565
CNN 3	7.78	25.23 %	0.06019	3.65387
CNN 4	7.54	24.74 %	0.06878	3.59017

CNN 2

- **CNN 2** = VGG-Face with Adam Optimizer

Observations

- The CNN 2 model has an MAE of 7.94 and MAPE of 25.50% a vast improvement from the baseline model on both metrics. The Test Set Accuracy is up to 8.466%. However, the Test Set loss increased which is not a good sign.
- Observing *Figure 3* and *Figure 4*, there is an early divergence of the Training Set from the Test Set which may indicate **more extreme overfitting** than the baseline model.

Fig 3. CNN2 Training Set / Test Set Loss

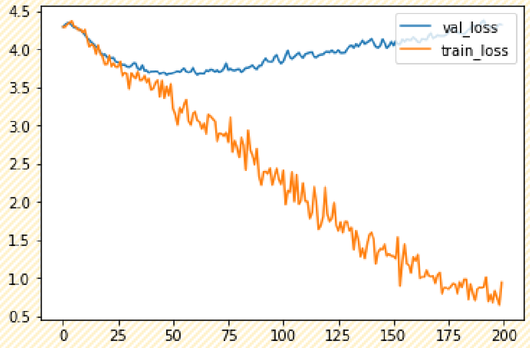
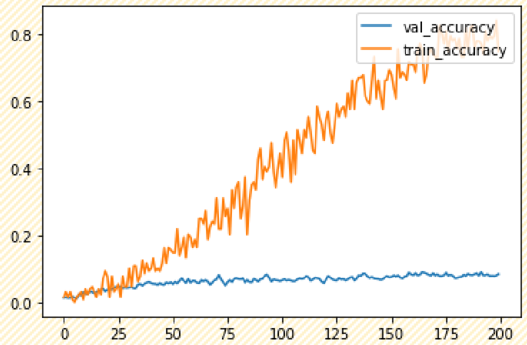


Fig 4. CNN2 Training Set / Test Set Accuracy



Test Set Model Performance Metrics

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CNN 4	7.54	24.74 %	0.06878	3.59017

CNN 3

- **CNN 3** = VGG-Face with Adam Optimizer with pretrained weights

Observations

- The CNN 3 model has a slightly improved MAE of 7.78, MAPE of 25.23% and Test Set Loss of 3.65387. However, the Test Set Accuracy has decreased to 6.019%.
- Again, *Figures 5* and *6* indicate **overfitting.**

Fig 5. CNN3 Training Set / Test Set Loss

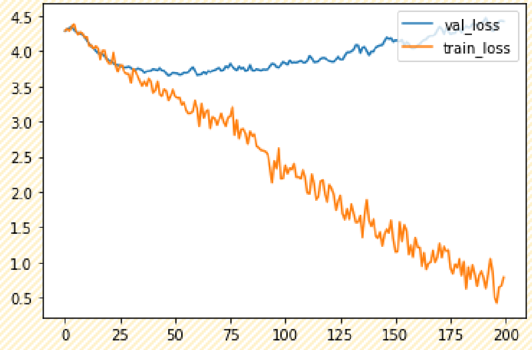
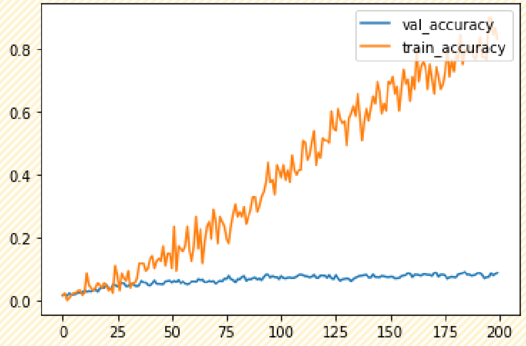


Fig 6. CNN3 Training Set / Test Set Accuracy



Test Set Model Performance Metrics				
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CNN 4	7.54	24.74 %	0.06878	3.59017

CNN 4

- **CNN 4** = VGG-Face with Adam Optimizer with pretrained weights & data augmentation

Observations

- The CNN 4 model has an improved MAE of 7.54, MAPE of 24.74% and Test Set Loss of 3.59017. The Test Set Accuracy has improved to 6.878%.
- In *Figure 7*, the Training Set Accuracy and the Test Set Accuracy moving together.
- Similarly, in *Figure 8*, the Training Set Loss and the Test Set Loss moving together until around 100 epochs.
- These are good signals that the **model is not overfitting.**
- We selected this as our **"best" model** to solve our age prediction problem.

Fig 7. CNN4 Training Set / Test Set Loss

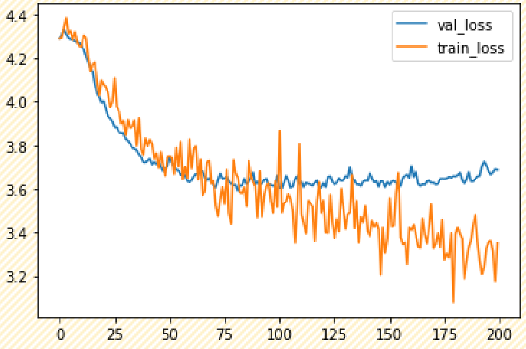
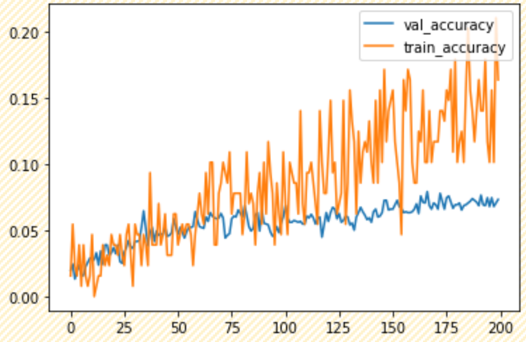


Fig 8. CNN4 Training Set / Test Set Accuracy



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Model Performance Comparison

Test Set Model Performance Metrics				
	MAE	**MAPE**	**Test Accuracy**	**Test Loss**
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CNN 2	7.94	25.50%	**0.08466**	4.31565
CNN 3	7.78	25.23 %	0.06019	3.65387
CNN 4	**7.54**	**24.74 %**	0.06878	**3.59017**

CNN 4 demonstrates the best performance on all metrics *except* Test Accuracy where CNN 2 performs best.

Business Results

- CNN 4 achieved an MAE of 7.54 years.
- The average age prediction is 7.54 years away from the actual value.
- The estimator can be improved with more balanced training data.

Photo by Markus Spiske on Unsplash

App Demo

Image 6. *Image of Dwayne Johnson.*

Predicted Age: 51

Actual Age: 48

Image 7. *Image of Celine Dion.*

Predicted Age: 61

Actual Age: 52

Image 8. *Image of Britney Spears.*

Predicted Age: 41

Actual Age: 34

App Demo

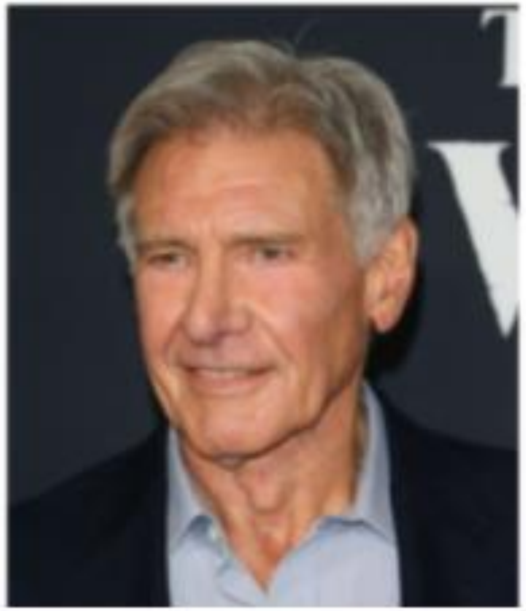

Image 9. *Image of Harrison Ford.*

Predicted Age: 66

Actual Age: 70

Image 10. *Image of Kim Kardashian.*

Predicted Age: 34

Actual Age: 37

Image11. *Image of Tom Hanks.*

Predicted Age: 64

Actual Age: 63

Conclusion

- We were able to create a functional image-based age predictor model using open-source software, a massive public dataset, and free cloud-based GPUs.
- *Python*, *TensorFlow*, *Keras*, *Google Colab*, etc., enable a very exciting world of AI innovation open to many people willing to learn.
- Public source code and public datasets further research and can enable new learners to develop faster.

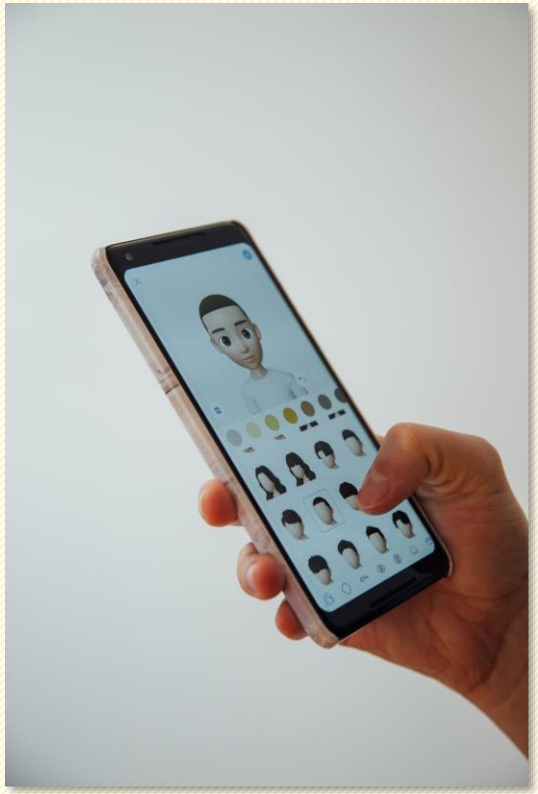

Photo by Charles Deluvio on Unsplash

Recommendations

- We recommend to our client that we create the beta version of our app with disclaimer that the model will be optimized over time.
- We recommend that we focus on high-quality and greater quantity of data to create a more robust predictor for a wider age range.
- We would like to do a survey of other pretrained models and how well they perform with our age prediction problem.

Photo by Isaac Quesada on Unsplash

Future Work

- **Data Acquisition** – expand data set to include more people age 0–8 and 81–100.
  - More high-quality data would increase the model's performance and generalizability
- Experiment with other pretrained CNN models and fine-tune the promising models

Photo by Egor Vikhrev on Unsplash

Lessons Learned

1. We are in a very exciting time in history where people can build impressive tools using open-source software.
2. Python, TensorFlow, Keras, Colab and public datasets can accomplish the seemingly impossible.
3. Class imbalance has been one of the most difficult challenges to overcome on this project. Downsampling and data augmentation were both used to address class imbalance.
4. Keep it simple. Beware of feature creep.

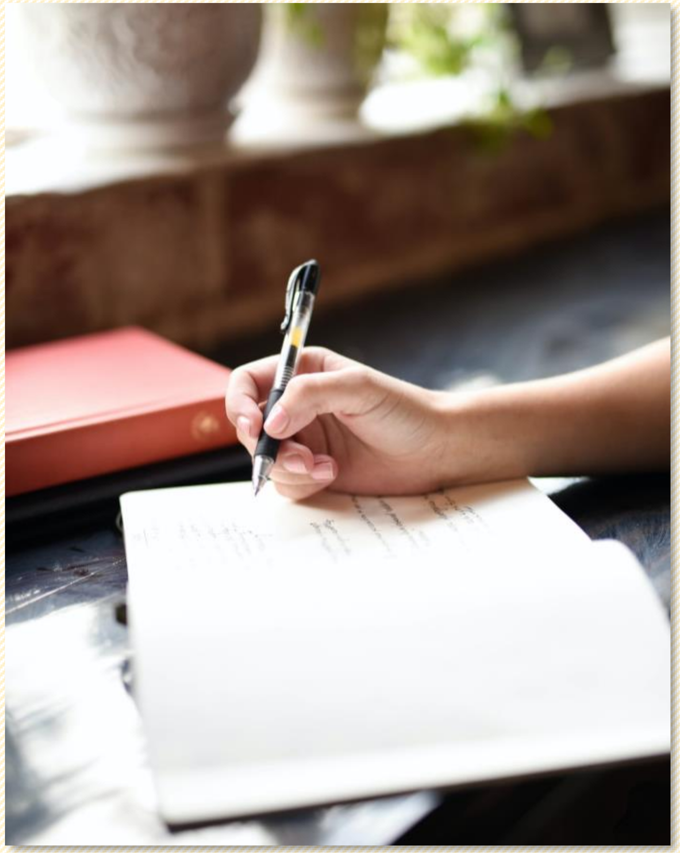

Photo by Hannah Olinger on Unsplash

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Also, my wife is pretty cool. Thank you for your inspiration, ***Pinky***!

Photo by Howie R on Unsplash

THANK YOU FOR YOUR TIME!

Question or Comments?

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