HIDING IN

PLAIN SIG

HARNESS

DEEP LEA

N

GHT:

SING

ARNING

Create
performance
off-the-sh
cla

Ex

01

OBJECTIVE

a high-quality dataset and analyze the
e of CNN architectures, transfer learning, and
elf tools to determine whether a CNN can
assify images of Morels in the wild.

xpert or novice?

02

METHODOLO

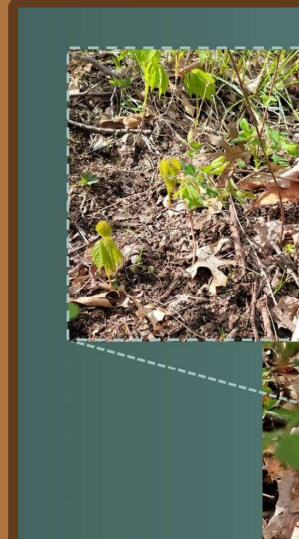
A significant portion of this
was to collect samples rep
where the mushrooms ma

- Dataset creation
  - Images were collect
    ensure quality and
    - Google image se
    - Facebook Morel
      publicly availabl
  - The remaining 398

OGY

s project focused on curating a high-quality datas
resentative of a typical forager's viewpoint. Sam
y not be obvious or even partially obscured.

ted in batches and then filtered to
representativeness.
earch (roughly 10% of the dataset)
l and foraging communities with
e media
images were manually sampled to



set from scratch. The goal
ples should include images

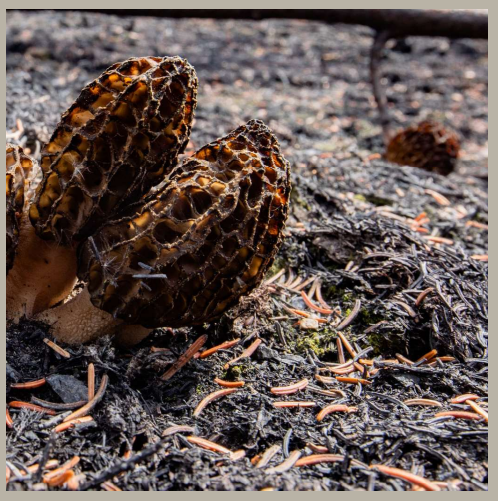
TO DETEC
MORELS I
NATURAL
SETTINGS

CT

IN

T

S



fig

I believe that crea

classes to repres

g 1. A few samples from the training set.

05

CONCLUSION

ating a more comprehensive data set that has
sent a greater diversity of the wildlife present

create the “morel” a
- The final dataset co
two evenly split clas

- Model Building
  - CNN architecture w
    - Overfit a small r
    - Systematically t
    - Apply data augr
  - Transfer Learning w
    - Followed a basi
    - MobileNetV2 wa
    foragers.
    - Given more time

- Teachable Machines
  - An off-the-shelf too
  learning rate.
  - I was able to produ
  mobile app, but du

and “none” classes
ontains 792 samples with
sses

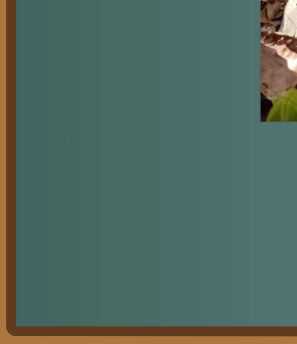


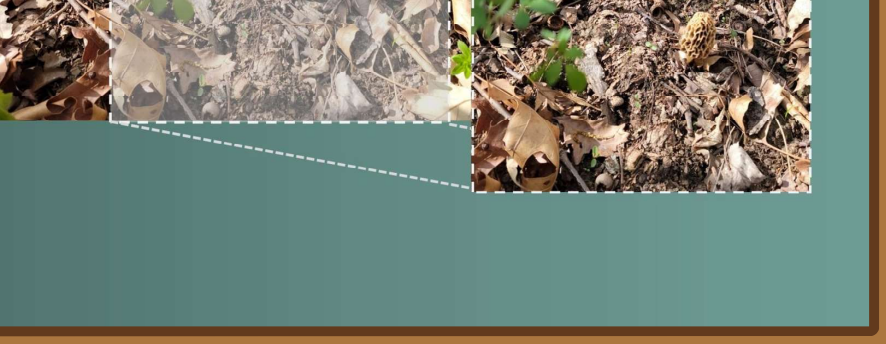
fig 2. T

vas explored with the following workflow:
model
est each hyperparameter to find an ideal model
mentation and regularization to improve accuracy
with MobileNetV2
c tutorial for transfer learning from tensorflow.or
as selected because there is potential to provide

e, I would have liked to explore this further.

l trained simply by uploading my dataset and a s

ce a model with very high accuracy and capabiliti
e to time constraints, I was not able to pursue thi



The image sampling process

y and reduce overfitting

rg
real-time assistance to

ignificant reduction in the

es to be deployed to a
s.

INTRODUCTION

Have you ever tried foraging fo
yes, you are probably familiar
infamous Morel. These mushro
known amongst foragers of all
cap of a morel features a disti
pattern that makes confident i
relatively simple but also make
notoriously difficult to find.
This characteristic presents an
problem for a computer vision
Consider that a novice forager
trouble seeing morels without
an expert, but once the novice
successful hunts, spotting ther
much more natural. It would a
simple matter of training the c

or wild foods? If
with the
ooms are well
l skill levels. The
nct honeycomb
dentification
es them

n interesting
n model to solve.
will often have
the guidance of
completes a few
m becomes
ppear to be a
ve to recognize

in a morel's ha
reliable predicti
with a large mod

It is worth notin
Object Detection
to detect hidden
I would have lik
protect, I think

AN

The biggest challe
I ultimately crea
project, which ulti

sent a greater diversity of the wildlife present
abitat could allow a model to provide more
ons. Of course, spending more time working
del, such as MobileNet may ultimately lead to
similar improvements.
g that there is a field of study; Camoflauged
is centered around how to best train a model
and obscured objects. If I had a bit more time
ed to explore some of that research for this
it would provide some interesting insight.

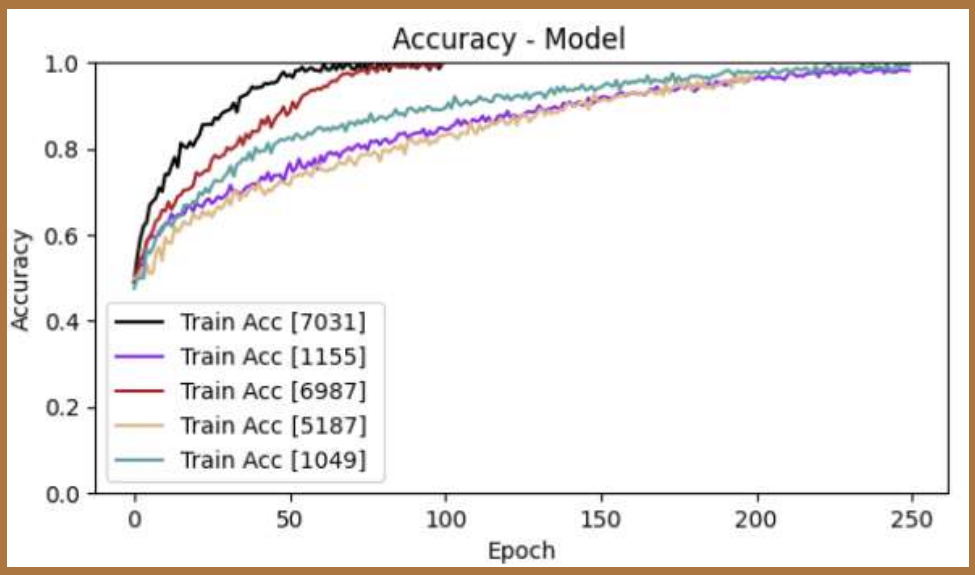
06

CHALLENGES
D FUTURE WORK

nge I faced in ths project was image sampling.
ated two fully independent datasets for this
mately ate up a significant portion of my time.

03 ANALYSIS

With the final dataset I was
space constraints I am not a
model was at overfitting, ev
noticeably stunts the mode
provide some more positive



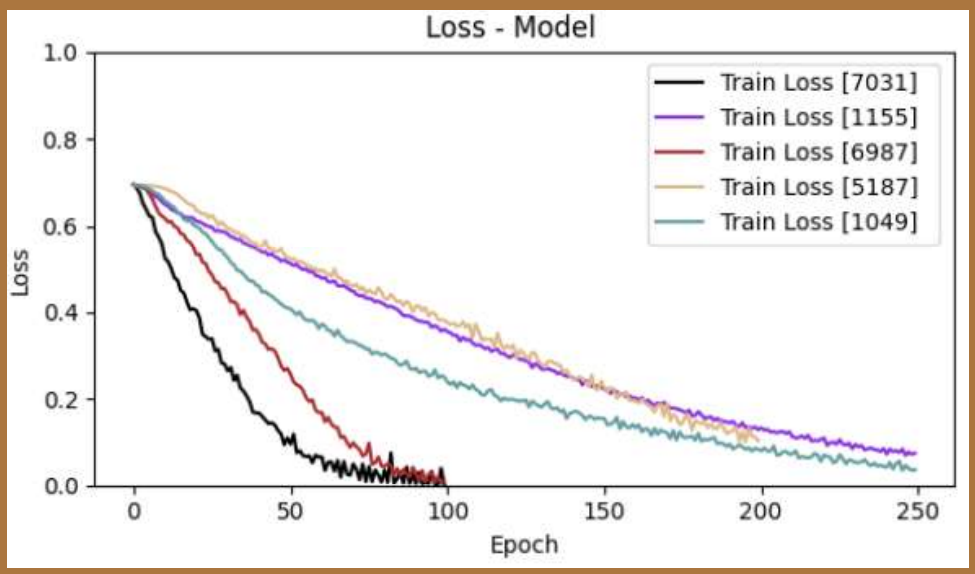
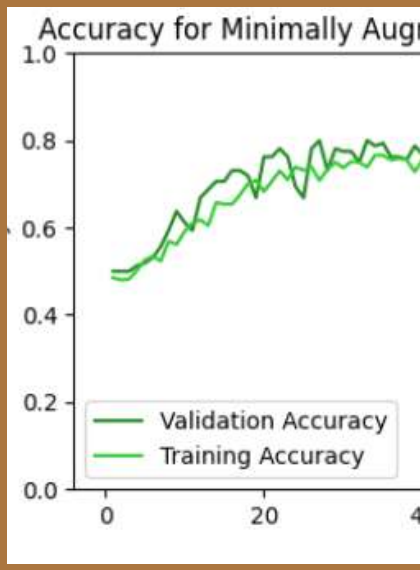


fig 3. Overfitting



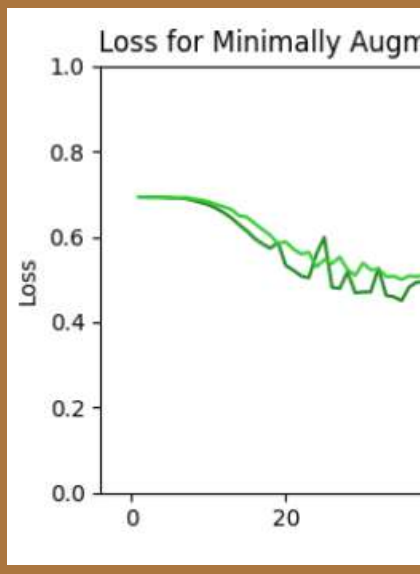
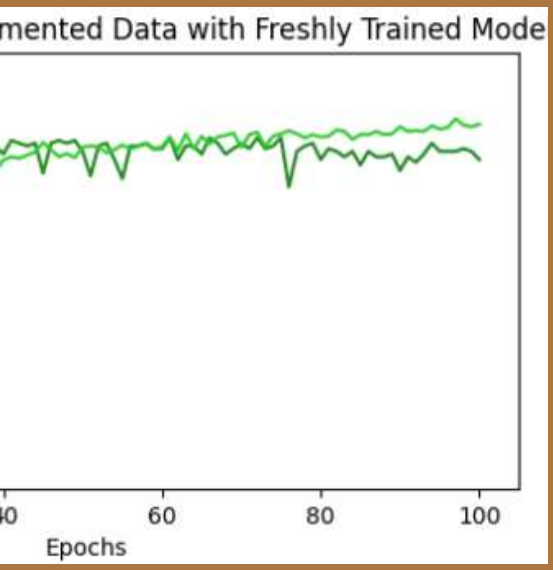
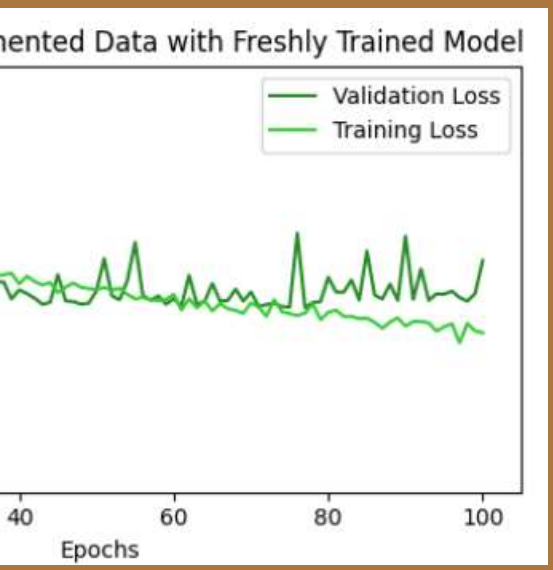


fig 4. Impact

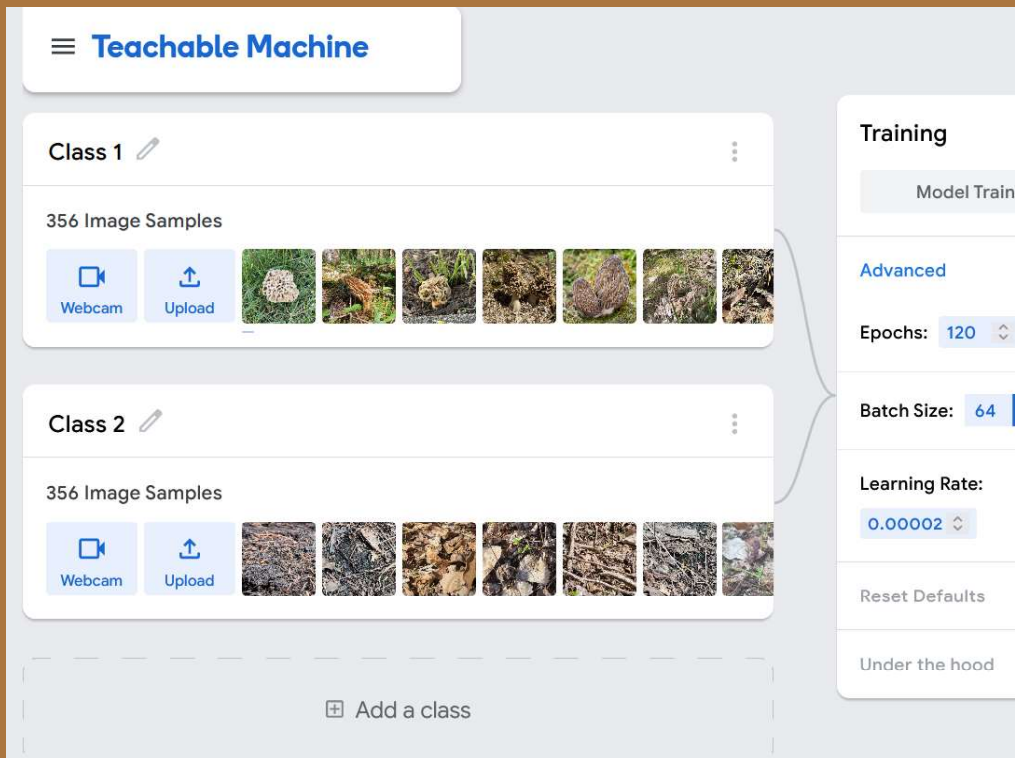
able to get reasonably good results in each stag
able to share all results here, but these results sh
en on a model of only 1049 parameters. Interest
el's ability to converge. Some more experimentat
e results. It is possible the model may still be a b





t of augmentation

This is a screenshot to highlig
from the Teachable Machine.
performs well, but the real in
interacting with the live came
may be stunting model perfo
scope.



e of development. Due to
how how successful the
tingly, augmentation
tion here may eventually
it too small.

ght the results I gathered
. The model clearly
sights were gained from
era. The dataset may be
rmance due to its narrow

simple matter of training the e
the pattern. Can a CNN learn t
forager too?

Author

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Affiliations

University of Missouri, St. Louis
Deep Learning, Spring 2024
Professor Badri Adhikari

eye to recognize
o be an expert

The second ite
performance incr

In the future I ho
the intersection
leveraged to educ

I believe this proj
tool that would e
Similar to tools su
the user in learn
than only levera

ration of the dataset did in fact show huge
reases, so the time spent seems to have been
worth while.

ope to expand on this idea. I am interested in
n of Artificial Intelligence and how it can be
cate and inspire users about the natural world
around them.

ect could be extended to a much broader use
educate users in the process of identification.
uch as iNaturalist, but with the goal to engage
ing about the wildlife in front of them rather
ging computer vision as a (powerful) search
engine.

04

RESULTS/FIN

Results suggest that, yes, a
spot morels hidden in the
Teachable machine, I do n
Despite the models' showc
evaluated with morel-spec
range of plant, fungi, and a
between a tree stump and
required.

fig 5. Teach

IDINGS

a convolutional neural network has the potential
natural landscape. However, after exploring pre
ot feel that this is something I am able to prove
casing high validation accuracy in several iteratio
cific data. In a real-world dataset, when the imag
animal matter, the model is ill-equipped to unde
l a morel. It is clear that further research and a m

able Machine

to learn how to reliably
dictive power with the
with my current dataset.
ons, they are only being
es encompass a full
rstand the nuances
more robust dataset is